Factorization Effect and Empirical Analysis of China's Industrial Carbon Emissions: Based on LMDI Model and STIRPAT Model

Yinping Jia, Longmei Shi, and Wenya Tan

Abstract—**The successful implementation of energy conservation and emission reduction policies relies on a systematic examination of the factors driving industrial carbon emissions. This study employs the Logarithmic Mean Divisia Index (LMDI) model to decompose carbon emissions and identify their primary determinants, enabling a quantitative evaluation of the key drivers behind industrial carbon emissions. The analysis utilizes energy consumption data from 30 Chinese provinces spanning the period from 2010 to 2022. To assess the effects of individual factors on industrial carbon emissions, a dynamic panel model within the STIRPAT framework is developed, using system GMM estimation. The results reveal distinct multi-stage variations in industrial carbon emissions, characterized by an overall increasing trend. Empirical evidence indicates that industrial population growth and economic development contribute to higher emissions, while innovation diffusion and energy structure adjustments play a significant role in mitigating them.**

Index Terms—**Industrial carbon emissions, LMDI decomposition model, STIRPAT model, Factor decomposition**

I. Introduction

As the world's largest industrial economy, China faces growing public scrutiny over its carbon emissions amid intensifying global climate challenges. The nation's green transition, propelled by climate change mitigation efforts and rapid industrialization, serves as a critical driver for establishing a low-carbon economy and achieving ecological civilization objectives. Notably, China contributes significantly to global low-carbon industry development, accounting for over 60% of worldwide new electricity generation from solar photovoltaics, wind power, and electric vehicle technologies. The proportion of solar photovoltaic and wind power in China's electricity generation mix has risen significantly from 4% in 2015 to 15% in 2023, achieving parity with levels in advanced economies. Furthermore, China's electric vehicle adoption rate now surpasses that of developed nations by more than twofold. Nevertheless, reconciling sustained economic expansion with meaningful emission mitigation continues to present a pressing challenge. Industrial carbon emissions are a key target of carbon reduction policies. By forecasting future carbon emission trends, governments and relevant authorities can proactively identify potential emission increases and formulate effective emission reduction policies and measures. Existing research by Guan et al. [1] indicates that variations in five key factors, namely industrialization level, technological advancement, energy intensity, industrial structure, and the energy sector, contribute to the spatial correlation of industrial carbon emissions, thereby influencing China's overall industrial carbon emissions. Arto Reiman et al. [2] argue that the Industrial Revolution created the foundation for technological advancement and identify key factors influencing industrial carbon emissions. Their study further investigates the dynamic evolution of China's industrial carbon emissions and associated policy interventions, with specific focus on industrial electricity consumption patterns and regional disparities in emission characteristics.

This study systematically decomposes the driving factors of China's industrial carbon emissions by integrating the LMDI and STIRPAT analytical frameworks. Additionally, the GM(1,1) grey prediction model is employed to forecast the future trends of industrial carbon emissions in China. Through empirical analysis, we quantify the relative contributions of key determinants and examine their temporal dynamics. Beyond environmental impacts, industrial carbon emissions present substantial socioeconomic challenges that warrant critical examination. Carbon-intensive industries are especially vulnerable to energy price volatility and regulatory shifts, which may increase operational costs and erode their competitive advantage in the market. This study yields critical insights into the intricate interplay between industrial expansion and carbon emissions in China, establishing an empirical basis for evidence-based emission mitigation policies. The results carry significant policy relevance for achieving China's "dual carbon" objectives while simultaneously promoting sustainable economic development.

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Yinping Jia is a master's student of Mathematics-Physics and Finance, Anhui Polytechnic University, CO 241000 China. (e-mail: 194821273@qq.com)

Longmei Shi is a lecturer at the School of Mathematics-Physics and Finance, Anhui Polytechnic University, CO 241000 China. (corresponding author to provide e-mail: shilongmei@ahpu.edu.cn).

Wenya Tan is a master's student of Mathematics-Physics and Finance, Anhui Polytechnic University, CO 241000 China. (e-mail: 2895275509@qq.com)

II. Literature Review

In pursuit of its ambitious "dual carbon" objectives, China has implemented progressively stringent emission regulations across all economic sectors in recent years. The escalating climate imperative has focused considerable research attention on identifying and analyzing the key drivers of carbon emissions. This has generated a substantial body of literature examining the determinants of industrial carbon emissions in China. Initial scholarly efforts predominantly addressed three critical dimensions: carbon efficiency optimization, emissions trading mechanisms, and the equitable distribution of emission rights [3]. Song et al. [4] employed the LMDI method to decompose the influencing factors of China's industrial carbon emissions from energy consumption into four key aspects: economic growth, energy intensity, energy structure, and industrial structure. The analysis reveals that although enhanced energy efficiency demonstrates a substantial mitigating effect on carbon emissions, economic expansion remains the predominant driver of emission growth, primarily through its direct correlation with elevated energy demand. By studying the spatiotemporal characteristics of industrial carbon emissions in China's Yangtze River Delta, Xu et al. [5] found that industrial carbon emissions have increased sharply, and adjusting the industrial structure can effectively reduce carbon emissions. Areepong and Karoon [6] developed the ARL formula to enhance the applicability of the seasonal autoregressive model, which is widely utilized in air pollution research. Furthermore, population dynamics play a crucial role in influencing carbon dioxide emissions, while economic conditions and activities significantly impact both energy consumption and carbon emissions. As a major economic power, China faces significant challenges in controlling carbon emissions from industrial enterprises [7], promoting the development of a low-carbon economy, and identifying key influencing factors to achieve its dual carbon goals.

Both SDA and IDA are widely employed to examine the drivers of carbon emissions, though methodological divergences persist across empirical applications. Among these, LMDI is the most widely applied method [8]. Using LMDI and Tapio decoupling models, Qu et al. [9] demonstrated that economic growth hinders industrial emission reduction and decoupling, whereas energy intensity and industrial structure act as key mitigating factors. Additionally, adjustments in the energy structure present significant potential for further reducing industrial carbon emissions. To inform global carbon policy decisions, Chen et al. [10] conducted a geographical analysis of provincial-level industrial emission drivers. Meanwhile, Ren and Zhao [11] employed the STIRPAT model to identify industrial technological capacity, per-capita industrial production, and population scale as the three dominant factors influencing China's industrial carbon emissions. Through gray prediction modeling, their analysis revealed that per-capita industrial production exerts the most substantial influence on industrial carbon emissions. Complementing this, Tu et al. [12] applied the LMDI decomposition approach to identify key determinants of emission intensity, demonstrating that declining energy intensity, as indicated by the decoupling model, plays a crucial role in driving China's industrial carbon emissions reduction.

This study adopts the LMDI model to decompose the driving factors of China's industrial carbon emissions from energy consumption, building upon established classification frameworks in the literature. To enhance analytical rigor, we complement the decomposition analysis with the STIRPAT model and system GMM approach, thereby improving the reliability and robustness of our findings. While existing research predominantly employs single-model approaches to investigate energy consumption and emission patterns, few studies have integrated multiple analytical frameworks. Our multi-method approach contributes to a more comprehensive understanding of emission drivers, providing valuable insights for achieving China's "dual carbon" objectives.

III. Research Methods

A. Carbon Emission Measurement

Industrial carbon emissions were calculated using energy consumption data spanning 2010-2022 across China's 30 provincial-level regions. The estimation incorporated ten key energy sources: coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, natural gas, coke oven gas, and liquefied petroleum gas. The methodology followed the estimation standards set by the Intergovernmental Panel on Climate Change [13]. The specific formulas applied are follows.

$$C_i = \sum_{i=1}^{n} B_i \times f_i \tag{1}$$

$$f_i = NCV_i \times CC_i \times COF_i \times \frac{44}{12} \tag{2}$$

Among these variables, C_i represents the total industrial carbon dioxide emissions resulting from the consumption of ten types of energy. B_i denotes the energy consumption of each province, converted into standard coal. f_i is the carbon dioxide emission coefficient, while NCV_i refers to the average net calorific value. CC_i represents the carbon content per unit of calorific value, and COF_i denotes the carbon dioxide emission factor. The term $\frac{44}{12}$ serves as the conversion coefficient from carbon atomic mass to carbon dioxide molecular mass.

B. LMDI Decomposition Model

Originally proposed by Japanese economist Yoichi Kaya, the Kaya identity has become a seminal analytical framework for decomposing the key factors influencing carbon emissions [14]. Building on the factor decomposition method proposed by Guo and Zhang [15], this study develop a tailored model for China's industrial carbon emissions that incorporates sector-specific structural characteristics. The following equation (3) represents an augmented Kaya identity that accounts for an expanded set of influential variables beyond the original formulation.

$$\begin{aligned} C \; &= \sum_i \frac{C_{it}}{E_{it}} \times \frac{E_{it}}{M_{it}} \times \frac{I_{it}}{GDP_{yit}} \times \frac{GDP_{yit}}{GDP_{it}} \times \frac{GDP_{it}}{P_{it}} \\ \times \quad P_{it} &= \sum_i s_{it} \times e_{it} \times d_{it} \times h_{it} \times f_{it} \times g_{it} \times p_{it} \end{aligned} \tag{3}$$

In this context, C represents China's industrial carbon emissions, where i denotes the 30 provinces and municipalities, and t represents the year. E refers to the total industrial energy consumption, while M denotes the number of enterprises above the designated size. I represents the number of effective invention patents held by industrial enterprises above the designated size. GDP_y corresponds to industrial added value, whereas GDP refers to the GDP, adjusted for price factors. P represents industrial employment. Due to the unavailability

TABLE I
DESCRIPTION OF FACTORS INVOLVED IN THE MODEL

Symbol	Meaning Note
C	Industrial carbon emissions
s	Energy mix
e	Energy intensive
d	Innovation distribution
h	Innovate efficiency
f	Industrial structure
g	Level of economic development
p	Number of people employed in industry

of direct industrial employment statistics, we adopt the National Bureau of Statistics' methodology by calculating industrial employment as secondary sector employment minus construction sector employment. Variable definitions are detailed in Table I.

Equation (4) presents the LMDI decomposition model for industrial carbon emissions derived from the extended Kaya identity in equation (3).

$$\begin{aligned} \Delta C &= C^t - C^0 = \Delta C_s + \Delta C_e + \Delta C_d \\ &+ \Delta C_h + \Delta C_f + \Delta C_g + \Delta C_P \end{aligned} \tag{4}$$

In equation (4), ΔC_s represents the energy mix, ΔC_e denotes energy intensity, ΔC_d refers to innovation distribution, ΔC_h signifies innovation efficiency, ΔC_f corresponds to industrial structure, ΔC_g reflects the level of economic development, and ΔC_p represents the number of people employed in industry. The LMDI decomposition method quantifies the contribution of each determinant factor to industrial carbon emissions, with the respective effect expressions provided in equation (5).

$$\begin{aligned} \Delta C_s &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{s_i^t}{s_i^0} \\ \Delta C_e &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{e_i^t}{e_i^0} \\ \Delta C_d &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{d_i^t}{d_i^0} \\ \Delta C_h &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{h_i^t}{h_i^0} \\ \Delta C_f &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{f_i^t}{f_i^0} \\ \Delta C_g &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{g_i^t}{g_i^0} \\ \Delta C_p &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{p_i^t}{p_i^0} \end{aligned} \tag{5}$$

C. STIRPAT Model

This study utilizes the STIRPAT model to examine the determinants of China's industrial carbon emissions. The STIRPAT model was developed by York et al. [16] as an enhanced version of the IPAT framework, overcoming its structural limitations. The model specification is presented below.

$$I = aP^b A^c T^d e \tag{6}$$

In this model, I represents the environmental impact, P denotes population size, A indicates the level of affluence, and T reflects the level of technology. The parameter a is the model coefficient, while b, c, d are the exponents to be estimated. The term e represents the error term.

The STIRPAT model, a well-established framework for emission analysis, shares conceptual foundations with the LMDI decomposition approach employed in this study. Building upon this theoretical alignment, we utilize the STIRPAT framework to examine the principal determinants of China's industrial carbon emissions. To account for China's distinctive socioeconomic and industrial context, we develop an augmented STIRPAT specification that incorporates country-specific modifying factors. As shown in equation (7).

$$\begin{aligned} \ln C &= \ln a + t \ln s + u \ln e + v \ln d + w \ln h \\ &+ x \ln f + y \ln g + z \ln p + \ln q \end{aligned} \tag{7}$$

C represents carbon emissions from industrial energy consumption. s is energy mix, e represent energy intensive, d reflects the level of innovation, measured by the ratio of the number of effective invention patents of industrial enterprises above the designated size to the total number of such enterprises, representing the technological level. h isinnovate efficiency, f reflects industrial structure, g is GDP per capita, calculated as the ratio of GDP to the industrial population (excluding price factors), represents the degree of affluence. p denotes the number of industrial employees, serving as the population size factor. The specific definitions of each factor correspond to Table I. a is the model coefficient, while t, u, v, w, x, y, z are the elasticity coefficients of each variable, indicating the percentage change in the dependent variable when the corresponding independent variable changes by 1%. q represents the error term.

D. Data Sources

This study examines industrial data spanning 2010-2022 across 30 Chinese provinces and municipalities. Due to data availability constraints, Tibet, Hong Kong, Macao, and Taiwan are excluded from the analysis. Primary data sources include official publications from China's National Bureau of Statistics (China Industrial Statistical Yearbook, China Energy Statistical Yearbook), the Wind financial database, and provincial statistical yearbooks. Table II displays the carbon emission factors and standard coal conversion coefficients for relevant energy sources, calculated following the Guidelines for Provincial Greenhouse Gas Inventories.

IV. THE RESULTS ANALYSIS

A. Industrial Carbon Emission Characteristics

China's industrial carbon emissions during 2010-2022 were calculated using Equations (1) and (2). To better characterize emission trends, we employ industrial carbon intensity (defined as total industrial carbon emissions divided by industrial value-added) as our primary metric, which reflects emissions per unit of industrial output. Using constant 2010 prices for industrial value-added calculations eliminates price fluctuation effects. The results are shown in Figure 1.

TABLE II
DISCOUNTED STANDARD COAL COEFFICIENT AND CARBON EMISSION COEFFICIENT OF MAJOR ENERGY SOURCES

Types of energy	Discounted standard coal factor	Carbon emission coefficient
Raw coal	0.7143	1.9
Coke	0.9714	2.86
Crude oil	1.4286	3.02
Gasoline	1.4714	2.93
Kerosene	1.4714	3.02
diesel	1.4571	3.1
Fuel oil	1.4286	3.17
Natural gas	1.33	2.07
Coke oven gas	6.143	0.76
Liquefied petroleum gas	1.7143	3.1

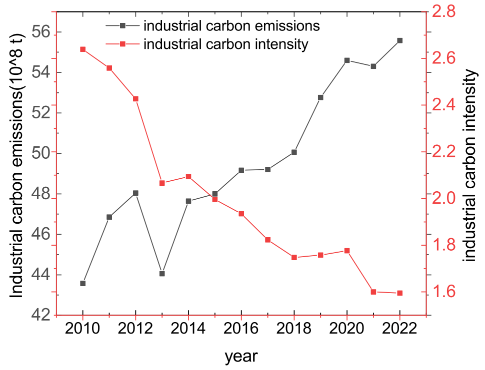

Fig. 1. China's industrial carbon emissions and carbon intensity.

Figure 1 demonstrates a general upward trend in global industrial carbon emissions, punctuated by a distinct decline in 2012 and subsequent recovery following the 2013 minimum. During this period, the Chinese government implemented multiple mitigation measures - including clean energy adoption and large-scale ecological initiatives - which contributed to decelerating the growth rate of industrial emissions. Despite the persistent increase in global atmospheric CO_2 concentrations during 2010-2022, China's proactive implementation of clean energy transitions and large-scale ecological programs substantially contributed to decelerating the growth rate of global CO_2 levels. Consequently, China has achieved near-zero growth in industrial carbon emissions while maintaining robust industrial output. This accomplishment coincides with measurable progress in climate change mitigation, as evidenced by a consistent decline in industrial carbon intensity during the 2010-2022 period. The observed decoupling of industrial production growth from emission trajectories reflects both enhanced energy efficiency and structural transitions toward environmentally sustainable industrial practices.

Figures 2-5 display the spatial distribution of China's provincial industrial carbon emissions for 2010, 2014, 2018, and 2022, respectively. Generated through ArcGIS spatial analysis, these thematic maps employ a five-tier classification scheme with graduated color shading, where darker hues correspond to higher emission intensities, enabling intuitive cross-provincial comparisons.

Comparative analysis of Figures 2-5 reveals distinct spatial

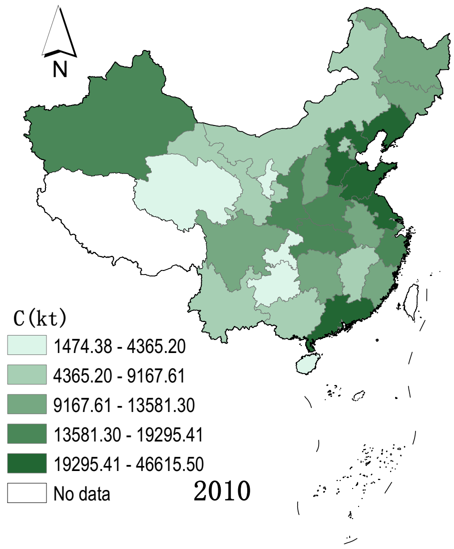

Fig. 2. Spatial characteristics of China's industrial carbon emissions in 2010

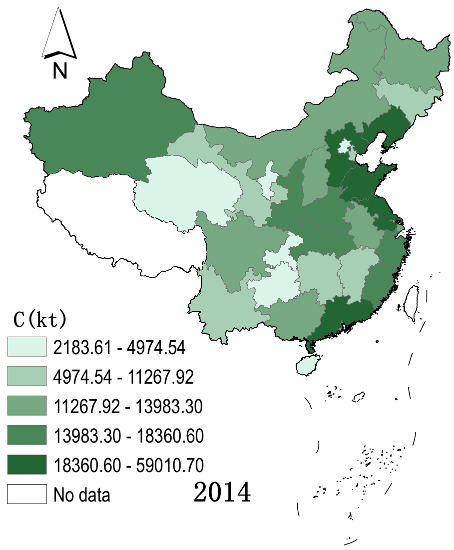

Fig. 3. Spatial characteristics of China's industrial carbon emissions in 2014

heterogeneity in China's industrial carbon emissions from 2010 to 2022, with consistently lower emission levels in central, western, and northeastern regions relative to eastern coastal areas. This spatial disparity principally stems from the eastern seaboard's geographic and economic advantages, which have concentrated energy-intensive industries through agglomeration effects. Consequently, this region exhibits advanced urbanization and industrialization, characterized by dense clustering of energy-intensive and heavy chemical industries. The resultant carbon emissions remain elevated due to these sectors' substantial fossil fuel consumption,

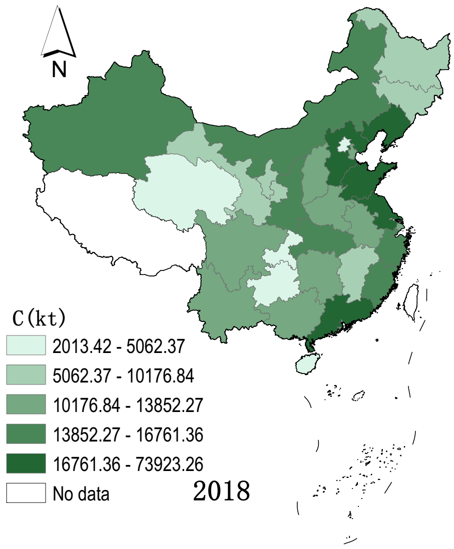

Fig. 4. Spatial characteristics of China's industrial carbon emissions in 2018

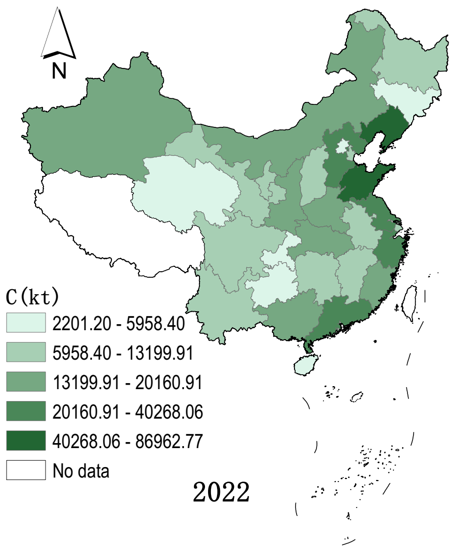

Fig. 5. Spatial characteristics of China's industrial carbon emissions in 2022

particularly coal and petroleum products. Furthermore, accelerating urbanization in these regions amplifies energy demand for both infrastructure expansion and transportation systems, thereby generating additional carbon emissions. The overall color intensity in the maps becomes darker, and regional polarization gradually decreases, reflects increasing national carbon emissions during 2014-2018. This period witnessed accelerated industrialization, yet persistent reliance on obsolete technologies and suboptimal industrial configurations contributed to rising sectoral emissions - a pattern corroborated by the temporal trends in Figure 1. By 2022, industrial carbon emissions demonstrated increasing spatial heterogeneity. While overall emissions continued to rise, emissions in most provinces started to decline. This reduction can be attributed to provinces' efforts to integrate resources, reduce the share of energy-intensive industries, regulate high-carbon-emission activities, and promote the modernization and optimization of industrial structures. These coordinated measures effectively advanced energy conservation, emission mitigation, and sustainable development objectives.

Overall, China's industrial carbon emissions exhibit a high proportion of characteristic patterns and a substantial total, as the country is still in the process of industrialization and relies heavily on energy, particularly coal and other fossil fuels. This emission profile stems from structural economic imbalances, wherein energy-intensive industries remain disproportionately prominent. Due to the considerable disparities in industrial carbon emissions between provinces, it is essential to promote interprovincial resource integration and technical collaboration to collectively reduce China's industrial carbon emissions.

B. Carbon Emission Projections

China's industrial carbon emissions exhibited an overall upward trend with notable fluctuations during 2010-2022. The initial period (2010-2012) saw rapid emission growth, primarily driven by robust economic expansion, intensified industrial activity, and elevated energy consumption. A temporary decline occurred in 2013, likely attributable to economic restructuring and strengthened environmental regulations. The subsequent phase (2014-2017) was marked by growth rate moderation and fluctuation as policy adjustments took effect. From 2018 onward, emissions resumed a steady upward trajectory, with particularly pronounced increases post-2018. The 2020-2022 period experienced anomalous emission patterns due to COVID-19 pandemic disruptions to industrial production systems.

China has pledged to achieve peak carbon emissions by 2030 and carbon neutrality by 2060. Predicting industrial carbon emissions can help assess current emission reduction progress, identify critical future milestones, and provide scientific support for the government in formulating effective carbon reduction pathways. Given the industrial sector's dominant contribution to national emissions, such forecasts enable targeted identification of high-emission industries and facilitate structural optimization. Moreover, emission trajectory modeling helps anticipate potential peak timing or rebound risks, thereby preventing economic instability from overzealous short-term mitigation measures. Accordingly, this study applies the GM(1,1) grey prediction model to forecast China's industrial carbon emissions (units: billion tons), with detailed results presented in Table III.

The close alignment between observed and predicted values demonstrates the model's strong predictive capability for tracking industrial carbon emission dynamics. Both datasets exhibit remarkably consistent upward trajectories, mirroring the sustained growth of emissions accompanying economic expansion. Projections for 2023-2035 indicate persistent emission growth, with significant increases anticipated beyond 2030. This trajectory suggests that

TABLE III
PREDICTED VALUES OF CHINA'S INDUSTRIAL CARBON EMISSIONS

Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Original value	43.58	46.86	48.04	44.06	47.65	48.00	49.17	49.20	50.10	52.76	54.60	54.30	55.58
Predicted value	43.58	45.15	45.98	46.83	47.70	48.57	49.47	50.38	51.31	52.25	53.21	54.20	55.20
Year	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
Predicted value	56.21	57.24	58.30	59.37	60.47	61.58	62.71	63.87	65.05	66.25	67.47	68.71	69.97

achieving China's peak emissions target will require accelerated implementation of three key measures: energy mix optimization, low-carbon technological innovation, and industrial structure upgrading. The findings further imply that realizing both the 2030 peak and 2060 neutrality targets may necessitate more stringent policy interventions.

C. LMDI Decomposition Results

To determine the contribution of each decomposition factor, this study utilized the additive LMDI factor decomposition method. The calculations were performed using Stata 17, based on formulas (3)-(5). A positive value indicates a driving influence on carbon emissions, while a negative value represents a mitigating effect. The strength of the driving force is reflected in the absolute value of the result. The decomposition results for the driving factors are presented in Table IV.

China's industrial carbon emissions demonstrate an overall increasing trend, primarily driven by three key factors: fossil fuel-dominant energy structure, innovation efficiency, and rapid economic development. However, emissions are being reduced by factors like energy intensity, innovation distribution, and industrial structure. The impact of industrial labor force size exhibits temporal variability, showing inconsistent directional effects. The aggregate positive drivers have outweighed mitigation factors, resulting in continued growth of industrial carbon emissions.

The decomposition analysis reveals distinct patterns among key drivers: economic expansion and energy efficiency improvements paradoxically emerge as dominant contributors to emission growth, whereas industrial restructuring and innovation diffusion demonstrate stronger mitigation effects. This pattern reflects China's persistent reliance on energy-intensive industries, particularly those dependent on raw coal combustion. Notably, the energy structure's impact remained positive in all study years except 2010 and 2011, consistently exacerbating industrial carbon emissions. The National Energy Administration's research indicates that 2011, marking the inception of China's 12th Five-Year Plan period, represented a transitional phase characterized by steady energy-economic growth and balanced demand-supply dynamics. Although the economy had not yet established a stable emissions-growth equilibrium, a gradual recovery persisted throughout 2011. Globally, the decelerated rise in carbon emissions correlated with increasing corporate patent filings, revealing a non-linear, complex relationship between industrialization and emission trajectories. This complexity stems from industrialization's dual effect of elevating energy demand and associated emissions, while enabling structural transitions that may accelerate emission growth during transitional phases.

As a core element of corporate intellectual property, innovation diffusion serves as both an indicator of technological competitiveness and a determinant of market positioning for knowledge-intensive enterprises. Contemporary research in energy and environmental management underscores innovation's pivotal role in energy intensity reduction, particularly through green technological advancements that substantially influence industrial emission patterns. Given the industrial sector's dominant contribution to national energy consumption and carbon output, technological innovation emerges as a critical pathway for achieving sustainable development objectives. Additionally, optimizing the industrial structure contributes to reducing industrial carbon emissions. This optimization not only significantly enhances green total factor productivity but also promotes improvements in energy efficiency.

The decomposition analysis further reveals the variable impact of industrial workforce dynamics on carbon emissions. While industrial employment growth typically elevates material consumption and associated emissions, parallel improvements in workforce education and technical skills can partially offset these effects. A system to reduce carbon emissions can be established by streamlining the industrial structure, enhancing energy efficiency, and transforming certain industries. These findings provide an empirical foundation for formulating evidence-based emission reduction policies.

In conclusion, this study identifies two pivotal strategies for industrial carbon mitigation: strengthening green innovation capacity, particularly in low-carbon technologies, and optimizing industrial structure through sectoral rebalancing. These policies foster efficiency improvements and technological advancements, both of which are crucial for ensuring the long-term sustainability of China's industrial sector.

D. Empirical Results of System GMM

This study investigates the determinants of China's industrial carbon emissions through an integrated econometric framework employing LMDI decomposition analysis. Yang et al. [17] employ the STIRPAT model and system GMM to explore the factors affecting industrial carbon emissions. A dynamic panel data model is developed based on the static model analysis and derived from the STIRPAT framework in equation (8), incorporating the dynamic persistence characteristics of carbon emissions.

$$\begin{aligned} \ln C &= \ln a + \theta L.\ln C + t\ln p + u\ln g + v\ln d \\ &+ w\ln s + x\ln e + y\ln h + z\ln f + \ln q \end{aligned} \tag{8}$$

The temporal dynamics of emission evolution are more precisely captured by including a one-period lagged

TABLE IV
LMDI DECOMPOSITION RESULTS OF INFLUENCING FACTORS OF CHINA'S INDUSTRIAL CARBON EMISSIONS FROM 2010 TO 2022

Year	Energy mix	Energy intensive	Distribution of innovations	Innovation efficiency	Industrial structure	Economic development	Population
2010-2011	-899.65	165633.6	-224065.1	14727.7	28668.06	33545.49	15181.17
2011-2012	244.40	-19341.25	-91782.82	88423.77	-10462.82	61677.89	-16900.84
2012-2013	3429.34	-76487.59	-46834.44	55832.61	-17052.63	28147.84	13128.10
2013-2014	4088.52	24432.61	-29269.8	16556.57	-15037.29	32504.31	2602.45
2014-2015	2080.62	1433.997	11402.55	-6411.075	-38678.48	57209.28	-23508.71
2015-2016	1053.11	32187.48	-79370.25	47084.05	-21064.34	45159.38	-13344.48
2016-2017	712.34	18637.12	-80767.58	25745.13	3308.542	47584.15	-14877.81
2017-2018	4259.21	-2267.677	-55974.82	32297.57	-1670.806	44226.50	-12329.26
2018-2019	920.05	40558.56	-76646.66	43476.57	-11731.17	46034.42	-15563.12
2019-2020	1157.65	-14005.54	-75919.89	108405.6	-14760.21	-1147.613	14617.49
2020-2021	754.79	-59387.29	-28470.05	-18984.38	62649.83	31927.98	8532.64
2021-2022	2575.10	-27112.44	-13858.88	22095.39	12580.89	37633.37	-21143.92

TABLE V
DESCRIPTIVE STATISTICAL RESULTS

Variables	Average	Standard deviation	Minimum	Maximum
lnC	13.11	0.07	12.98	13.23
lnp	5.92	0.98	3.77	7.78
lng	3.79	0.52	2.7	5.48
lnd	4.23	0.7	2.27	6.73
lns	0.92	0.1	0.52	1.1
lne	4.22	0.83	2.42	6.3
lnh	5.16	0.7	3.23	6.66
lnf	3.59	0.28	2.58	4.22

term of industrial carbon emissions in the regression specification, thereby accounting for persistence effects in the emission trajectory [18]-[19]. $L.\ln C$ denotes the industrial carbon emissions lagged by one period [20].The dynamic specification demonstrates superior methodological rigor and empirical validity relative to static counterparts, as it explicitly accounts for temporal dependencies inherent in emission processes. The analysis accounts for multiple determinants of industrial carbon emissions, including both modeled and extraneous factors [21]. The incorporation of lagged variables serves to mitigate the influence of uncontrolled covariates, thereby improving the empirical robustness of the regression estimates. Table V presents the descriptive statistics for all model variables.

The empirical analysis employs the system GMM estimator, implemented through both one-step and two-step approaches [22]-[24]. The AR(1) and AR(2) tests are conducted to check for serial correlation in the random disturbance terms, while the Hansen test is used to assess the validity of the instrumental variables. The p-value of the Hansen test, ranging from 0.1 to 0.25 as shown in Table VI(3), indicates that the instrumental variables are valid. The lack of second-order autocorrelation in the model is confirmed by the p-value of AR(1), which is less than 0.01, and the p-value of AR(2), which is greater than 0.1, thereby validating the GMM model statistics. The conclusions from the two-step estimation are presented in Table VI, which includes the random effects regression(1), fixed effects regression(2), and the GMM two-step estimation results(3).

TABLE VI
EMPIRICAL RESULTS

Variables	re	fe	GMM
L.lnC			0.224**
			(2.08)
lnp	0.025***	0.198***	0.143**
	(5.20)	(10.49)	(2.52)
lng	0.0632***	0.220***	0.148 ***
	(6.59)	(13.58)	(3.29)
lnd	-0.069***	-0.028*	-0.130**
	(-5.83)	(-1.93)	(-2.2)
lns	-0.151***	-0.077	-0.44**
	(-4.22)	(-1.44)	(-2.05)
lne	0.019***	0.015	0.073*
	(2.76)	(1.42)	(1.82)
lnh	-0.029**	-0.013	-0.107
	(-2.23)	(-0.84)	(-1.57)
lnf	0.002	0.01	0.014
	(0.17)	(0.53)	(0.17)
Constant	13.214***	11.265***	9.913***
	(78.55)	(33.75)	(6.62)
Sample size	390	390	360
AR(1) p-value			0.001
AR(2) p-value			0.617
Hansen p-value			0.196

The findings in Table VI indicate that the energy structure and innovation distribution significantly reduce carbon emissions across the fixed effects, random effects and system GMM models. The degree of technological advancement, as reflected in the distribution of innovation, suggests that higher levels of innovation are associated with lower industrial carbon emissions. These findings are consistent with the innovation diffusion effects identified in the LMDI decomposition analysis. The energy structure effect, which is calculated as the ratio of industrial carbon emissions to total industrial energy consumption, captures the intensity of carbon emissions per unit of energy consumed in industrial operations, reflecting the efficiency of energy use in the industrial sector. Furthermore, the lagged industrial carbon emissions coefficient is significantly positive, indicating that industrial carbon emissions exhibit persistence [25]. This temporal dependency suggests that industrial carbon emissions exhibit notable inertia, wherein historical production patterns and energy use behaviors continue to influence future emission trajectories.

Industrial carbon emissions demonstrate significant dependence on both workforce scale and economic development levels. Expansion of the industrial labor force precipitates intensified production activity, which in turn elevates energy demand and associated carbon emissions.With more workers involved in manufacturing processes, the demand for raw materials, intermediate goods, and final products rises, requiring additional energy to support production equipment and operations. As a result, industrial carbon emissions are substantially amplified, particularly in energy-intensive foundational industries like steel and cement production that underpin economic modernization. As economic development progresses, the demand for material goods continues to grow, driving up industrial output and energy consumption, both of which are major contributors to carbon emissions. The composition of industrial sectors constitutes a critical determinant of carbon emissions, particularly due to the disproportionate environmental impact of energy-intensive industries. Structural transitions within these sectors may initially elevate emissions before yielding long-term mitigation benefits-a phenomenon observed in heavy manufacturing and primary material production. This challenge persists within the broader context of global emission escalation trends. Energy intensity, which refers to the total energy used per unit of industrial production, also has a significant impact on carbon emissions. Although energy efficiency in China has improved, technological advancements may have a greater influence on economic growth than on energy conservation and emission reduction, potentially leading to an overall increase in carbon emissions. To effectively reduce industrial carbon emissions, it is essential to leverage market processes and implement a comprehensive set of emission reduction policies. These measures will not only support sustainable and high-quality economic development but also contribute to the reduction of carbon emissions.

V. Conclusions And Policy Recommendations

To validate the observed marginal changes, Yupaporn Areepong and Kotchaporn Karoon [26] proposed an autoregressive model based on the DEWMA technique, a method widely employed in economic studies involving real-world data. This study examines the influence of multiple determinants using industrial data from China. Specifically, it estimates industrial carbon emissions across Chinese provinces using energy consumption data and applies the Kaya identity to construct an LMDI decomposition model. This model decomposes carbon emissions into key driving factors, including population size, industrial structure, economic development, innovation efficiency, energy structure, energy intensity, and spatial distribution. Additionally, a dynamic panel model is developed within the STIRPAT framework, incorporating system GMM estimations to analyze the effects of these factors on industrial carbon emissions.

The analysis based on the grey system theory's GM(1,1) grey prediction model indicates that, under current development trajectories, China's industrial carbon emissions will continue to rise steadily. The model's results show that from 2023 to 2035, industrial carbon emissions will experience significant growth. These projections highlight a considerable gap between existing emission reduction policies and the dual-carbon targets. To meet the strategic goals of reaching carbon peaking by 2030 and achieving carbon neutrality by 2060, it is crucial to accelerate industrial restructuring and upgrading, promote energy system transformation, enhance carbon pricing mechanisms, and foster innovation and application of green technologies. A comprehensive policy approach is necessary to achieve meaningful progress in the industrial sector's low-carbon transition.

The LMDI decomposition results reveal that China's industrial carbon emissions are primarily driven by the energy structure effect, innovation efficiency effect, and economic development effect, all of which exert positive influences. In contrast, the energy intensity effect, innovation distribution effect, and industrial structure effect contribute to emission reductions. Notably, the impact of industrial population size on carbon emissions remains statistically inconclusive. A more detailed analysis shows that economic growth and energy efficiency play dominant roles in increasing emissions, while industrial restructuring and innovation distribution serve as more significant mitigating forces. Overall, the positive drivers outweigh the negative ones, leading to an overall increase in China's industrial carbon emissions.

Within the STIRPAT framework, industrial carbon emissions are used as a proxy for environmental pressure, encompassing all relevant component factors. A dynamic regression analysis is conducted using the GMM estimator, with results compared against conventional regression models. The analysis reveals a significant persistence effect in China's industrial carbon emissions, as evidenced by the strongly positive coefficient of the lagged emissions term. Furthermore, the findings indicate that innovation distribution and energy structure contribute to emission reductions, while industrial population size and economic development level have significant positive effects, thereby driving carbon emissions upward.

Based on the findings from the regression analysis and decomposition model, this study presents policy recommendations organized into three key dimensions.

First, enhancing innovation capacity and transitioning to cleaner energy systems should be prioritized. Key measures include accelerating the integration of renewable energy sources, such as wind and solar power, across industrial sectors to reduce dependence on fossil fuels. Additionally, implementing stringent carbon intensity standards, particularly for energy-intensive industries in China's more developed eastern regions, is essential. Strengthening institutional support for research and development, as well as fostering collaboration between research institutes and enterprises, will be crucial for accelerating the commercialization of low-carbon technologies.

Second, the dual objectives of enhancing industrial productivity while decarbonizing production processes must be pursued in tandem. Given the empirically established positive relationship between economic growth and emissions, particular emphasis should be placed on improving energy efficiency during periods of economic expansion. To mitigate emissions, optimizing supply chain management is crucial. This can be achieved through the adoption of green logistics, the optimization of transportation routes, and the promotion of a low-carbon revolution throughout the entire supply chain. Furthermore, industrial enterprises must develop and implement comprehensive environmental management strategies that prioritize waste reduction and resource recycling. Employee engagement and training are also essential for raising awareness of environmental protection and energy conservation, thereby fostering a cultural shift towards sustainability within organizations.

Third, at the national level, China must proactively fulfill its international climate commitments, strengthen collaboration with the global community, and jointly address the pressing challenge of climate change. The country should establish and enforce rigorous industrial carbon emission standards, foster the development and adoption of low-carbon technologies and clean energy, and incentivize enterprises to transition to green practices. Concurrently, regulatory oversight and evaluation mechanisms must be bolstered to ensure the effective implementation of policies and measures, ultimately achieving carbon peak and carbon neutrality within the industrial sector. These recommendations aim to substantially reduce carbon emissions while advancing sustainable industrial development.

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