

Article

Sustainable Industrial Development in China: Decomposition of Green Total-Factor Productivity and Identification of Innovative Provinces

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Abstract

Green development has become a strategic imperative for China amid increasing environmental constraints and economic restructuring, representing a critical pathway toward industrial sustainability. This study develops a global Malmquist index framework based on a slacks-based measure under the assumption of variable returns to scale to evaluate the dynamic evolution of industrial green total-factor productivity (GTFP) in 30 Chinese provinces from 2006 to 2022. To identify the key drivers of changes in GTFP, the index is decomposed into pure technical efficiency, scale efficiency, and technological change components. The empirical findings yield four main insights. First, the distribution of green development efficiency shifted from a relatively uniform pattern during the 11th and 12th Five-Year-Plan periods to a pyramid-shaped distribution during the 13th Five-Year-Plan period, indicating growing regional disparities. Second, China's industrial GTFP exhibited a consistent downward trend over the study period, primarily attributable to deteriorations in pure technical and scale efficiencies, despite the positive contributions from technological progress. Third, we observe a structural risk of a central lag in GTFP: the eastern provinces demonstrate superior pure technical efficiency, while the western provinces exhibit relatively higher scale efficiency. By contrast, technological progress appears spatially balanced. Fourth, industrial innovation is not prominent during the periods 2018–2019 and 2021–2022. These findings have policy implications for promoting regional coordination and enhancing innovation-driven strategies to advance China's green industrial transformation.

Keywords: industrial sustainability; green total-factor productivity; green development efficiency; climate change; slacks-based measure



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1. Introduction

Climate change, energy shortages, and pollution all necessitate the pursuit of green development, making it an important direction for global economic transformation. As the world's largest energy consumer, second-largest economy, and largest carbon emitter, China faces the dual challenges of resource constraints and environmental pressure [1]. In 2024, China introduced the 2024–2025 Energy Conservation and Carbon Reduction Action Plan and Opinions on Accelerating the Comprehensive Green Transformation of Economic and Social Development. Then, in 2025, it issued the Implementation Opinions

on Building Pilot Zones for a Beautiful China. Such policies reflect China's commitment to green development.

Industry is a major consumer of energy [2]. Figure 1 illustrates the changing trends in energy consumption in industry and six other sectors from 1980 to 2022. We can see that, overall, both the absolute and relative amounts of industrial energy consumption have been increasing. In 1980, industrial energy consumption was 1.831 times that of the other six sectors combined; by 2022, it had increased to 2.053 times. Consequently, a pressing challenge emerges: how to reduce energy consumption, carbon emissions, and pollution from industry while maintaining economic growth. In this context, measuring industrial green development efficiency (GDE) and assessing green total-factor productivity (GTFP) based on GDE have become particularly important.

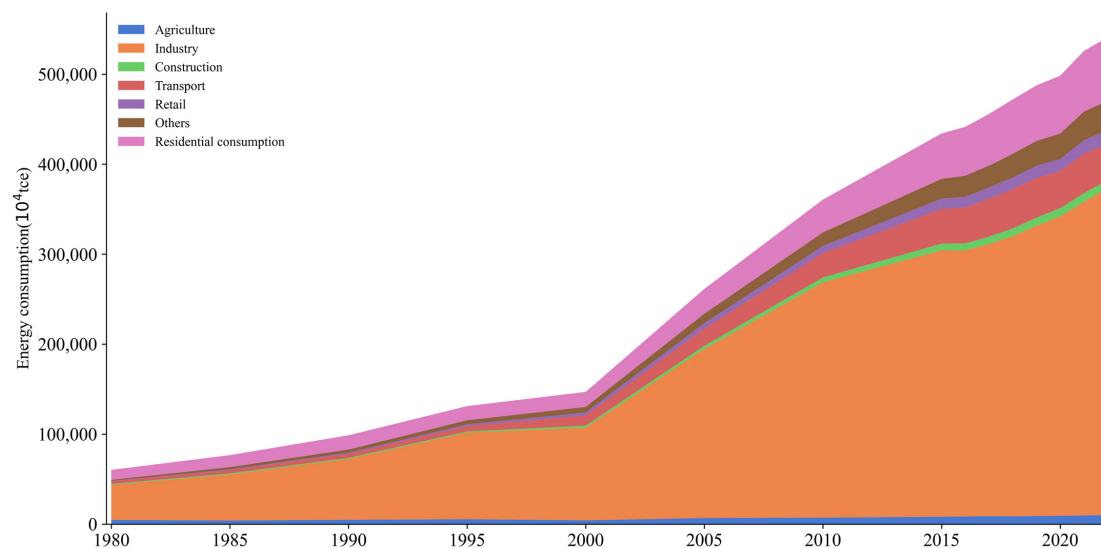


Figure 1. Energy consumption by sector, 1980–2022.

GTFP is an important indicator for measuring the relationship between economic development and environmental impact, serving as a quantitative proxy for progress toward industrial sustainability and the Sustainable Development Goals (SDGs)—particularly SDG 9 (Industry, Innovation and Infrastructure) and SDG 12 (Responsible Consumption and Production) [3]. It reflects dynamic changes in the efficiency of an economy's production processes under resource and environmental constraints. Recently, there has been an increase in research on GTFP [4,5] and its related theories and methods. In such work, data envelopment analysis (DEA), combined with the Malmquist index, has become an important way to assess changes in GTFP [6,7].

Among the methods that combine DEA and the Malmquist index, the directional distance function (DDF) is the most commonly used approach for DEA. However, DDF calculation typically relies on a predetermined direction vector, and the choice of this vector directly affects the efficiency assessment results [8,9]. Regarding the selection of the Malmquist index, studies mainly use the geometric mean of two adjacent contemporaneous Malmquist indices. However, this approach faces the potential problem of infeasibility in linear programming. Moreover, it is not circular, meaning it cannot measure the cumulative effect of GTFP over time.

This study mainly addresses three questions: (1) How can we measure changes in GTFP and its cumulative effects over time in China's industrial sectors without arbitrarily projecting decision-making units (DMUs) onto the frontier? (2) Which factors (management level, scale, and TC) drive or hinder the GTFP of China's provincial industrial sectors during the period 2006–2022? (3) What are the dynamic changes and regional differences in

GTFP and its decomposition (PTE, SE, and TC) in China's industrial sectors, both recently and in the long term? To answer these questions, we construct a Malmquist index using a slacks-based measure (SBM) model and perform decomposition analysis under variable returns to scale (VRS). VRS can decompose GTFP more finely and identify the suitability of the industrial production scale in each province. The aim is to provide theoretical support and policy guidance for the green transformation of China's industrial sectors.

2. Literature Review

Most studies have employed DEA models to evaluate industrial GDE from a static perspective (i.e., using cross-sectional data to measure industrial GDE). Some have focused on specific aspects of industrial GDE, such as carbon dioxide (CO₂) [10], the environment [11], or energy [12]. Others have evaluated the indicators of industrial GDE, which some studies refer to as “eco-efficiency” [13], while others term it as “energy and environmental efficiency” [14], “energy economic efficiency” [15], or “green economic efficiency” [16].

With the maturing of static industrial GDE assessment techniques, studies are increasingly using DEA window analyses to evaluate industrial GDE. Such approaches enable temporal information to be incorporated into the efficiency results, which can then be used in conjunction with econometric methods to investigate the relationship between industrial GDE and related factors. For example, Jabari et al. [17] studied the effects of economic sanctions on industrial energy efficiency in Iran, while Wang et al. [18] examined how industrial upgrading affects China's industrial eco-efficiency. Yan et al. [19], meanwhile, investigated the effect of city size on industrial land-use efficiency in China.

Studies have combined DEA models with the Malmquist index to analyze the temporal dynamics of industrial GDE—that is, changes in total-factor productivity. The Malmquist index is a widely recognized indicator that measures changes in total-factor productivity. GTFP incorporates environmental factors such as sulfur dioxide (SO₂) and CO₂ into the Malmquist index measurement framework. Chung et al. [20] considered undesirable outputs based on DDF, incorporating environmental factors into the Malmquist index measurement framework. They called this new index the Malmquist–Luenberger productivity index. Subsequent GTFP-related research mainly adopted combinations of DDFs and the Malmquist index, continuously amending the research methods. For instance, Zhang and Choi [21] proposed combining metafrontier DDF with the Malmquist index to measure GTFP. They decomposed GTFP into three factors: efficiency change, best-practice gap change, and technology gap change. To address the issue of using arbitrary directions to project DMUs to the frontier in previous studies, Arabi et al. [22] and Arabi et al. [23] introduced slack variables into DDF to measure GTFP.

Regarding the measurement of industrial GTFP, relevant studies remain relatively scarce. Table 1 lists some representative recent studies, from which we can observe the following: (1) In early studies, when measuring total-factor productivity, researchers used the Charnes, Cooper, and Rhodes model (CCR) without considering undesirable outputs in combination with the Malmquist index. As pollution issues emerged, researchers began to combine DDF, which is considered undesirable output, with the Malmquist index to measure industrial GTFP. However, the DDF method requires pre-specifying a directional vector, and the choice of this directional vector directly affects the measurement results. Another type of DEA model (SBM) can also handle undesirable outputs and does not require setting arbitrary directions to project DMUs to the frontier before model solving. This has been applied in a few cases to assess GTFP in other fields, such as the Xiang River basin cities [24] and the Pearl River Delta urban agglomeration [25]. However, an SBM-based Malmquist index has yet to be applied to China's industrial sectors. (2) Most studies assess industrial GTFP and decompose its driving factors into TC and technical

efficiency under the assumption of constant returns to scale (CRS). However, no studies have decomposed it into PTE, SE, and TC under VRS. (3) The majority of studies focus on industry subsectors as their research objects. The study periods are either too short or too far in the past, resulting in findings with limited implications for policy and decision-making. There remains a significant research gap in terms of focusing on industrial sectors across China's provinces, particularly in identifying innovators and tracking their dynamic evolution over extended periods.

Table 1. Representative literature on the evaluation and decomposition of industrial GTFP.

Author (Year)	DMUs	Period	DEA Model	Decomposition	Identify Innovators
Shestalova [26]	OECD countries for manufacturing industries	1970–1990	CCR	Efficiency change, TC	×
Chen and Golley [27]	38 industrial subsectors in China	1980–2010	DDF	Efficiency change, TC	×
Fan et al. [28]	32 industrial subsectors in Shanghai (China)	1994–2011	DDF	Efficiency change, TC	✓
Yao et al. [29]	Chinese provinces for industrial sectors	1998–2011	DDF	Efficiency change, best-practice gap change, T gap change	×
Emrouznejad and Yang [30]	30–31 manufacturing subsectors in China	2004–2012	DDF	PTE, TC, SE	×
Emrouznejad and Yang [31]	17–18 light manufacturing subsectors in China	2004–2012	DDF	PTE, TC, SE	×
Ding et al. [32]	China's Yangtze River Delta region for industrial sectors	2012–2017	DDF	Efficiency change, TC	×
Wang et al. [33]	34 industrial subsectors in China	2005–2015	DDF	Efficiency change, TC	×
Zhu et al. [34]	41 industrial subsectors in China	2013–2016	DDF	Efficiency change, TC	×
This study	Chinese provinces for industrial sectors	2006–2022	SBM	PTE, TC, SE	✓

Note: ✓ indicates that the work was relevant to the issue; × means the work was unrelated.

The main innovations of this study are as follows: (1) Our study is the first to use an SBM-based Malmquist index to evaluate GTFP in China's provincial industrial sectors. When measuring a cross-period SBM model, linear programming may potentially be infeasible in the geometric mean form of the Malmquist index. To address this, we construct an SBM-based global Malmquist index (SBM-GMI) to measure GTFP. (2) We decompose SBM-GMI into three components: PTE, SE, and TC. Compared with most studies, this allows for a more detailed identification of the factors affecting changes in China's industrial GTFP. (3) This study is the first to examine recent GTFP trends in China's provincial industrial sectors from a long-term perspective, using data spanning 17 years. We not only identify annual innovators but also identify disparities between regional industrial sectors. In this way, we aim to propose targeted strategies for fostering green development in China's diverse industrial landscape.

3. Method

3.1. SBM Model with Undesirable Outputs

The three types of indicators for production-efficiency measurement include (1) inputs (e.g., energy and capital), (2) desirable outputs (e.g., industrial added value), and (3) undesirable outputs (e.g., industrial waste gas, wastewater, carbon emissions). Production-

efficiency measurement regards capital, labor, and capacity as inputs [10,29], assuming that less is better regarding these indicators. Since desirable and undesirable outputs are positive and negative indicators, respectively, the final undesirable outputs can be assumed to be strongly disposable [35]. Based on the characteristics of inputs and outputs, the following formula represents our proposed production possibility set:

$$P = \left\{ (x, y, b) : \sum_{j=1}^n \lambda_j x_{ij} \leq x_{io}, \sum_{j=1}^n \lambda_j y_{ij} \geq y_{io}, \sum_{j=1}^n \lambda_j b_{ij} \leq b_{io} \right\},$$

where P represents the production possibility set, x represents inputs, y represents the desirable outputs, and b represents the undesirable outputs. Thus, based on the production possibility set, we develop an SBM model to measure production efficiency, as follows:

$$\begin{aligned} \beta_0 = \text{Min.} & \left[\frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_{io}^-}{x_{io}}}{1 + \frac{1}{l+e} \left(\sum_{i=1}^l \frac{s_{io}^+}{y_{io}} + \sum_{i=1}^e \frac{s_{io}^{b-}}{b_{io}} \right)} \right] \\ \text{s.t.} & \sum_{j=1}^n \lambda_j x_{ij} + s_{io}^- = x_{io}, i = 1, \dots, m \\ & \sum_{j=1}^n \lambda_j y_{ij} - s_{io}^+ = y_{io}, i = 1, \dots, l \\ & \sum_{j=1}^n \lambda_j b_{ij} + s_{io}^{b-} = b_{io}, i = 1, \dots, e \\ & s_{io}^-, s_{io}^+, s_{io}^{b-} \geq 0 \end{aligned} \quad (1)$$

$$\sum_{j=1}^n \lambda_j = 1. \quad (2)$$

The CRS assumption posits that all DMUs exhibit proportional changes in inputs and outputs. VRS, meanwhile, relaxes this assumption by introducing a convexity constraint (Equation (2)), allowing the production frontier to account for scale inefficiency; this enables the separation of pure technical efficiency from scale efficiency. Given the significant heterogeneity in provincial industrial development across China, the VRS assumption better aligns with reality. Equations (1) and (2) represent a constrained nonlinear programming problem, which needs to be transformed into a constrained linear programming problem for solving, as shown in Equation (3) [36]. Equations (1) and (2) and Equation (3) have the same solution, but their decision variables are correlated, where $\Lambda = \lambda t$, $S^- = s^- * t$, $S^+ = s^+ * t$, $S^{b-} = s^{b-} * t$:

$$\begin{aligned} \beta_0 = \text{Min.} & \left[t - \frac{1}{m} \sum_{i=1}^m \frac{S_{io}^-}{x_{io}} \right] \\ \text{s.t.} & \sum_{j=1}^n \Lambda_j x_{ij} + S_{io}^- = x_{io} t, \quad i = 1, \dots, m \\ & \sum_{j=1}^n \Lambda_j y_{ij} - S_{io}^+ = y_{io} t, \quad i = 1, \dots, l \\ & \sum_{j=1}^n \Lambda_j b_{ij} + S_{io}^{b-} = b_{io} t, \quad i = 1, \dots, e \\ & t + \frac{1}{l+e} \left(\sum_{i=1}^l \frac{S_{io}^+}{y_{io}} + \sum_{i=1}^e \frac{S_{io}^{b-}}{b_{io}} \right) = 1 \\ & S_{io}^-, S_{io}^+, S_{io}^{b-} \geq 0 \end{aligned} \quad (3)$$

3.2. SBM-Based Global Malmquist Index (SBM-GMI)

GDE, measured by the improved SBM model with undesirable outputs, is static and cannot compare GDEs across different periods. Therefore, we still use the Malmquist index to capture dynamic changes in GDE (referred to as the GTFP change index). We decompose this index into PTE, TC, and SE indices to reveal the factors affecting GTFP change.

Most studies, however, measure the Malmquist index based on the production technology sets of two adjacent periods. This approach involves cross-period comparisons, which can lead to infeasible solutions when evaluating a province in period $t + 1$ against a production frontier formed by provinces from period t , as the evaluated provinces might not be within the production possibility set [37]. In addition, the measured Malmquist index lacks transitivity, meaning $M^{t,t+2} = M^{t,t+1} \times M^{t+1,t+2}$. To overcome the defects of the adjacent-period Malmquist index—and considering that industry in China has undergone a long-term evolutionary process with multiple policy adjustments—we employ the global-period Malmquist index to provide a unified, time-invariant efficiency benchmark for the 17-year sample period [38]. The GMI for province o can be expressed using Equation (4) [24]:

$$M_c^g(z_o^{t+1}, x_o^{t+1}, y_o^{t+1}, b_o^{t+1}, z_o^t, x_o^t, y_o^t, b_o^t) = \frac{\beta_c^g(z_o^{t+1}, x_o^{t+1}, y_o^{t+1}, b_o^{t+1})}{\beta_c^g(z_o^t, x_o^t, y_o^t, b_o^t)}. \quad (4)$$

$\beta_c^g(z_o^k, x_o^k, y_o^k, b_o^k)$, $k = t, t + 1$ is the SBM distance between period k and the frontier of the global production possibility set, which is calculated using Equation (5) for each o :

$$\beta_c^g(z_o^k, x_o^k, y_o^k, b_o^k) = \min \left[\frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_{kio}^-}{x_{kio}}}{1 + \frac{1}{l+e} \left(\sum_{i=1}^l \frac{s_{kio}^+}{y_{kio}} + \sum_{i=1}^e \frac{s_{kio}^{b-}}{b_{kio}} \right)} \right],$$

$$\text{s.t.} \quad \begin{aligned} \sum_{t=1}^T \sum_{j=1}^n \lambda_j z_{kij} &= z_{kio}, i = 1, \dots, h \\ \sum_{t=1}^T \sum_{j=1}^n \lambda_j x_{kij} + s_{kio}^- &= x_{kio}, i = 1, \dots, m \\ \sum_{t=1}^T \sum_{j=1}^n \lambda_j y_{kij} - s_{kio}^+ &= y_{kio}, i = 1, \dots, l \\ \sum_{t=1}^T \sum_{j=1}^n \lambda_j b_{kij} + s_{kio}^{b-} &= b_{kio}, i = 1, \dots, e \\ s_{kio}^-, s_{kio}^+, s_{kio}^{b-} &\geq 0 \end{aligned} \quad (5)$$

$M_c^g > 1$, $M_c^g = 1$, and $M_c^g < 1$ represent progress, no change, and regression in GTFP, respectively. To better understand the reasons for changes in GTFP, this index can be decomposed into indices of efficiency change and TC [39], as shown in Equation (6):

$$\begin{aligned} M_c^g(z_o^{t+1}, x_o^{t+1}, y_o^{t+1}, b_o^{t+1}, z_o^t, x_o^t, y_o^t, b_o^t) &= \frac{\beta_c^g(z_o^{t+1}, x_o^{t+1}, y_o^{t+1}, b_o^{t+1})}{\beta_c^g(z_o^t, x_o^t, y_o^t, b_o^t)} \\ &= \frac{\beta_c^{t+1}(z_o^{t+1}, x_o^{t+1}, y_o^{t+1}, b_o^{t+1})}{\beta_c^t(z_o^t, x_o^t, y_o^t, b_o^t)} \times \left(\frac{\beta_c^g(z_o^{t+1}, x_o^{t+1}, y_o^{t+1}, b_o^{t+1}) / \beta_c^{t+1}(z_o^{t+1}, x_o^{t+1}, y_o^{t+1}, b_o^{t+1})}{\beta_c^g(z_o^t, x_o^t, y_o^t, b_o^t) / \beta_c^t(z_o^t, x_o^t, y_o^t, b_o^t)} \right) \\ &= EC_c \times TC_c \end{aligned} \quad (6)$$

EC_c represents the change in technical efficiency under CRS. Each of the three kinds of situations—that is, $EC_c > 0$, $EC_c = 0$, and $EC_c < 0$ —denotes an increase, no change, and a decrease in technical efficiency, respectively. TC_c denotes the change in the best-practice gap between T_c^g and T_c^k ($k = t, t + 1$), which demonstrates the progression of contemporary technology toward globally adopted technology. T_c^k represents the technology level in

period k . $TC_c > 1$, $TC_c = 1$, and $TC_c < 1$ represent technological progress, technological stagnation, and technological regression, respectively. Under VRS, efficiency change can be further decomposed into PTE and SE. For PTE, $PTE > 1$, $PTE = 1$, and $PTE < 1$ denote improvement in management level, no change in management level, and decline in management level, respectively. Similarly, for SE, $SE > 1$, $SE = 1$, and $SE < 1$ indicate scale optimization, no change in scale, and scale deterioration, respectively.

$$EC_c = \frac{\beta_c^{t+1}(z_o^{t+1}, x_o^{t+1}, y_o^{t+1}, b_o^{t+1})}{\beta_c^t(z_o^t, x_o^t, y_o^t, b_o^t)} = \frac{\beta_v^{t+1}(z_o^{t+1}, x_o^{t+1}, y_o^{t+1}, b_o^{t+1})}{\beta_v^t(z_o^t, x_o^t, y_o^t, b_o^t)} \times \frac{\beta_c^{t+1}(z_o^{t+1}, x_o^{t+1}, y_o^{t+1}, b_o^{t+1}) / \beta_v^{t+1}(z_o^{t+1}, x_o^{t+1}, y_o^{t+1}, b_o^{t+1})}{\beta_c^t(z_o^t, x_o^t, y_o^t, b_o^t) / \beta_v^t(z_o^t, x_o^t, y_o^t, b_o^t)} \quad (7)$$

$$= PTE \times SE$$

4. Data Description

This study focuses on 30 provinces, direct-controlled municipalities, and autonomous regions (excluding Tibet owing to data unavailability) in China for the period 2006–2022. CO₂ data are sourced from the Carbon Emission Accounts and Datasets (CEADs). Since the CO₂ data in this database have only been updated through 2022, our data coverage ends in 2022. This timeframe spans three Five-Year Plans in China: the 11th, 12th, and 13th. Each Five-Year Plan is a long-term national strategy that sets goals and directions for the country's economic development. By tracking historical data over this timeframe, we aim to identify the factors affecting GTFP changes across different historical periods. This long-term perspective allows for a more thorough and comprehensive investigation of the trends and determinants of GTFP change in China's various provinces.

Each province invests resources, including energy, capital, and labor, to generate gross regional product (GRP) while also emitting pollutants or CO₂. Based on this, we can use energy consumption, capital stock, and the total number of employees in industrial enterprises as proxy variables for energy, capital, and labor, respectively [40]. SO₂ emissions and chemical oxygen demand (COD) serve as proxies for pollutants. Table 2 presents the descriptive statistics for the three regions we consider in this study: eastern, central, and western China. The eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region comprises Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western region consists of Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

Table 2. Descriptive statistics of the inputs and outputs of 30 provinces in China, 2006–2022.

Region	Variable	Unit	Average	Standard Deviation	Minimum	Maximum
Eastern	Capital	10 ⁸ yuan	38,969.60	46,071.15	490.46	211,813.45
	Energy	10 ⁴ tce	4603.53	3895.84	107.89	14,292.60
	Labor	10 ⁴ persons	497.27	424.36	10.61	1568.00
	GRP	10 ⁸ yuan	12,100.11	9839.04	217.55	42,883.36
	SO ₂	10 ² tons	4282.36	4569.20	7.99	16,870.00
	COD	tons	91,028.92	97,027.91	1335.00	358,180.91
	CO ₂	tons	330.50	252.72	13.77	876.79
Central	Capital	10 ⁸ yuan	35,084.37	33,338.02	1500.53	171,959.73
	Energy	10 ⁴ tce	4014.87	1556.89	1266.91	8394.86
	Labor	10 ⁴ persons	255.76	133.39	72.71	724.19
	GRP	10 ⁸ yuan	6526.59	3499.82	1659.29	14,726.42
	SO ₂	10 ² tons	4372.59	3571.44	355.52	14,640.00
	COD	tons	92,250.13	74,707.97	3547.00	317,937.41
	CO ₂	tons	267.32	114.12	93.08	597.17

Table 2. Cont.

Region	Variable	Unit	Average	Standard Deviation	Minimum	Maximum
Western	Capital	10 ⁸ yuan	15,693.05	14,972.04	589.52	68,131.66
	Energy	10 ⁴ tce	2670.77	1424.95	346.04	7886.21
	Labor	10 ⁴ persons	112.24	83.36	14.60	391.44
	GRP	10 ⁸ yuan	3568.60	2741.76	265.12	13,454.11
	SO ₂	10 ² tons	4270.94	3359.43	368.37	13,840.00
	COD	tons	82,564.40	103,846.73	1552.00	679,464.38
	CO ₂	tons	197.87	146.17	17.97	830.79

Energy consumption and capital stock are calculated indirectly. Energy consumption is the sum of 13 energy types (raw coal, cleaned coal, other washed coal, coke, crude oil, fuel oil, gasoline, kerosene, diesel, liquefied petroleum gas, refinery gas, natural gas, and coke oven gas) multiplied by their respective conversion factors from physical units to coal equivalent [28]. Capital stock is calculated using Equations (8) and (9) [41], where K represents capital stock, I represents industrial gross investment, δ represents the capital depreciation rate, A represents accumulated depreciation, O represents the original price of fixed assets, and t represents the year.

$$K_t = I_t + (1 - \delta_t)K_{t-1}, \quad (8)$$

$$\delta_t = (A_t - A_{t-1})/O_{t-1}. \quad (9)$$

Industrial gross investment and GRP are deflated to 2006 constant prices. We use the regional price indices for fixed investment to deflate industrial gross investment and the regional industrial producer price indices to deflate GRP. SO₂ emissions and COD emissions are cited from the China Statistical Yearbooks on the environment, while CO₂ emissions are obtained from CEADs [42–44]. The four indicators (regional price indices for fixed investment, industrial gross investment, regional industrial producer price indices, and GRP) are all derived from the China Statistical Yearbooks. The number of enterprise employees, accumulated depreciation, and original price of fixed assets are obtained from the China Industrial Statistical Yearbook, while consumption data for the 13 types of energy are cited from the China Energy Statistical Yearbook.

5. Results and Discussion

5.1. Efficiency Results and Analysis

We use MATLAB R2024a to calculate Equation (1) under VRS, yielding the static industrial GDE for China from 2006 to 2022. The natural-breaks classification method is used to categorize China's average static industrial GDE from 2006 to 2022, as shown in Figure 2d. Beijing, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Guangdong, Qinghai, and Hainan have the highest industrial GDE; most of these are located in the southeastern coastal region. Fujian, Henan, Hebei, and Inner Mongolia have medium efficiency (yellow). Sichuan, Yunnan, Chongqing, Heilongjiang, Hunan, Hubei, and Shaanxi are in regions with relatively low efficiency (brown). Xinjiang, Gansu, Ningxia, Liaoning, Jilin, Guangxi, Guizhou, Jiangxi, Shanxi, and Anhui have the lowest efficiency (light purple). Since static industrial GDE is not suitable for comparison between different years, we do not compare industrial GDE across different years.

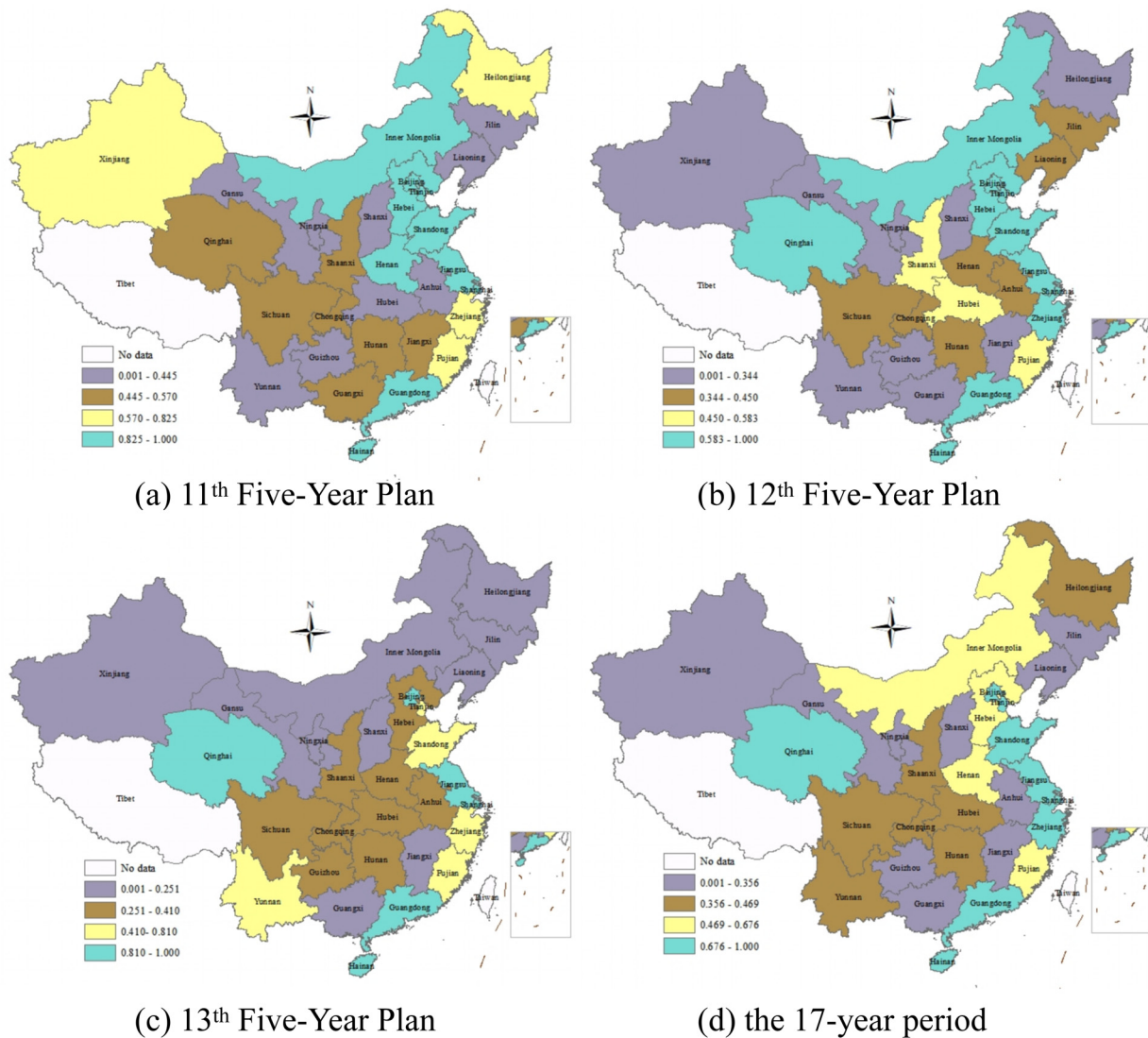


Figure 2. Average GDE for three Five-Year-Plan periods and the overall average for the 17-year period.

Further comparing the average industrial GDE during the 11th (2006–2010), 12th (2011–2015), and 13th (2016–2020) Five-Year-Plan periods, we use natural-breaks classification to categorize the 30 provinces, as shown in Figure 2a–c. We find that the layouts over the course of the 11th and 12th Five-Year Plans are relatively similar, with a comparable number of provinces in each category. During the 11th Five-Year-Plan period, the number of provinces with the highest, medium, relatively low, and the lowest efficiency is 10, 4, 7, and 9, respectively; for the 12th Five-Year-Plan period, the numbers are 11, 3, 7, and 9. By the 13th Five-Year-Plan period, however, the pattern changes significantly: The number of provinces with the highest, medium, relatively low, and the lowest efficiency becomes 6, 5, 9, and 10, respectively. This shift indicates that the distribution of industrial GDE gradually transitioned from a uniform distribution pattern over the course of the 11th and 12th Five-Year-Plan periods to a pyramid-shaped distribution during the 13th Five-Year-Plan period.

During the 13th Five-Year-Plan period, environmental regulations became increasingly stringent, especially with the passage of the Environmental Protection Tax Law in 2016 (formally implemented in 2018) and the launch of carbon-emission trading pilots in Fujian and Sichuan in 2016. These comprised critical institutional nodes that drove the restructuring of industrial GDE distribution patterns. Specifically, the differentiated environmental tax rate design (e.g., 1.2–12 yuan per pollution equivalent for air pollutants and 1.4–14 yuan for

water pollutants) significantly increased compliance costs for heavy-polluting provinces. Meanwhile, the coexistence of quota-allocation methods (baseline method and historical intensity method) produced asymmetric cost effects across different provinces. These two institutional innovations generated a compounding effect during the 13th Five-Year-Plan period: The developed eastern regions, leveraging their technological reserves and first-mover advantages in industrial structure, maintained higher GDE levels through green technology adoption and energy structure optimization with lower compliance costs. Meanwhile, resource-based provinces in the central and western regions, constrained by path dependence on traditional high-carbon industries, faced the dual squeeze of increased environmental tax burdens and rising carbon-reduction costs, resulting in lagging or even declining GDE improvements, thereby forming a pyramid-shaped distribution pattern.

5.2. Industrial GTFP and Its Decomposition

Some studies have used the arithmetic mean method to calculate average annual GTFP [45,46]. However, this measurement approach does not satisfy the condition that the average PTE multiplied by the average SE and the average TC equals the average GTFP. Appendix A shows the results of the arithmetic mean method used in this study. Given that the geometric mean is less sensitive to extreme values and is suitable for ratio-type data and considering that this study measures the Malmquist index as the rate of change in GTFP, we use the following approach: after calculating GTFP, PTE, SE, and TC from 2007 to 2022 using SBM-GMI, we employ the geometric mean method to compute the average values of GTFP, PTE, SE, and TC for each province, as shown in Figure 3.

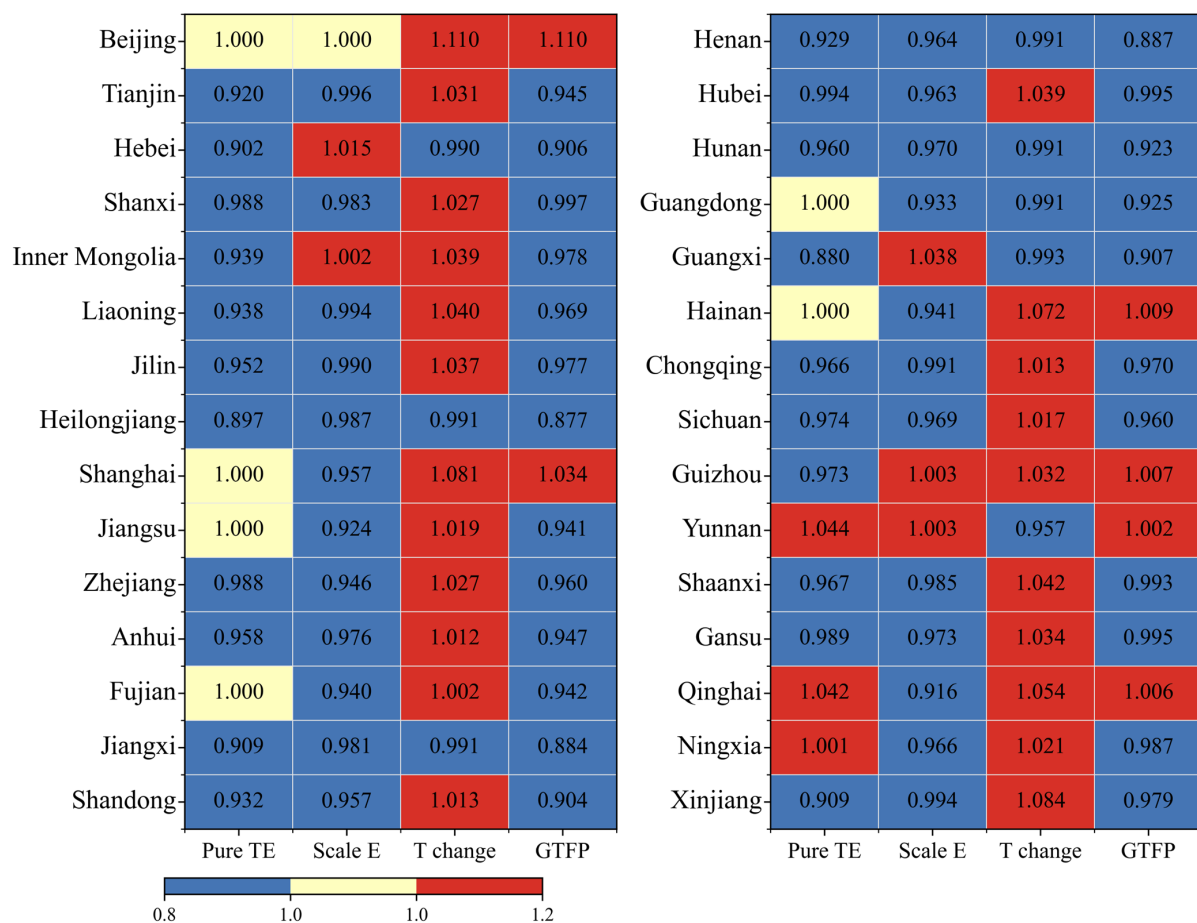


Figure 3. Weighted geometric mean of GTFP and its decomposition across 30 provinces. **Note:** E denotes efficiency, T denotes technology.

As illustrated in Figure 3, the driving factors of GTFP exhibit pronounced structural differentiation among the 30 provinces. In terms of contribution, TC is the primary growth engine, with 22 provinces recording TC indices greater than 1. Among them, 17 provinces (Tianjin, Shanxi, Inner Mongolia, Liaoning, Jilin, Jiangsu, Zhejiang, Anhui, Fujian, Shandong, Hubei, Chongqing, Sichuan, Shaanxi, Gansu, Ningxia, and Xinjiang), despite positive TC, still have a GTFP below 1 owing to the drag of PTE and SE. PTE generally shows stagnation or deterioration, with only nine provinces achieving PTE indices greater than or equal to 1 (Yunnan at 1.044, Qinghai at 1.042, Ningxia at 1.001, and six provinces—Beijing, Shanghai, Jiangsu, Fujian, Guangdong, and Hainan—at exactly 1.000), while the remaining 21 provinces all fall below 1. SE likewise performs poorly, with only five provinces exceeding 1—Hebei (1.015), Inner Mongolia (1.002), Guangxi (1.038), Guizhou (1.003), and Yunnan (1.003)—while the remaining 25 provinces are all below 1. Among the six provinces achieving GTFP growth, the driving patterns can be categorized into four types: Beijing represents a TC single-driver model (with TC at 1.110 and both PTE and SE at 1.000). Shanghai and Hainan exemplify a TC-led but SE-constrained model (Shanghai's TC is 1.081, PTE 1.000, and SE 0.957; Hainan's TC is 1.072, PTE 1.000, and SE 0.941). Qinghai demonstrates a PTE and TC dual-driver model but with constrained SE (PTE at 1.042, TC at 1.054, and SE at 0.916). Guizhou shows a TC and SE dual-driver model but with constrained PTE (TC at 1.032, SE at 1.003, and PTE at 0.973). Yunnan exhibits a PTE and SE dual-driver model but with constrained TC (PTE at 1.044, SE at 1.003, and TC at 0.957). Among the remaining 24 provinces with declining GTFP, 13 experience positive TC offset by the dual drag of PTE and SE. Four provinces (Heilongjiang, Jiangxi, Henan, and Hunan) face negative effects from all three factors—TC, PTE, and SE.

It is worth noting that Qinghai achieves a GTFP of 1.006, representing marginal growth among the 30 provinces, with its driving forces exhibiting typical characteristics of being “PTE-led with SE drag.” In terms of contribution, PTE at 1.042 ranks second nationally, only below Yunnan (1.044), providing a positive contribution of 4.2% to GTFP. However, SE stands at merely 0.916, ranking last among all provinces and creating a negative drag of 8.4%. TC (1.054) provides a positive support of 5.4%, with the three factors combined yielding a marginal GTFP growth of 0.6%. This extreme divergence pattern of “second in PTE, last in SE” reflects Qinghai's unique economic development model as an ecologically fragile area on the Qinghai–Tibet Plateau: On the one hand, strict environmental protection red lines have achieved significant improvements in PTE through refined regulation and institutional optimization. On the other hand, Qinghai's weak industrial foundation—in 2021, its industrial GRP ranked second to last, accounting for only 1.72% of top-ranked Guangdong's—coupled with a small industrial scale and insufficient factor inputs, has led to pronounced diminishing returns to scale, making SE the greatest weakness dragging down GTFP. This “high efficiency, small scale” growth model indicates that while Qinghai has improved its green development quality through technical efficiency enhancement, it has yet to overcome the bottleneck of scale.

Based on the GTFP, PTE, SE, and TC of 30 provinces in China from 2007 to 2022, we calculate the weighted geometric mean of these indices for the 30 provinces (using each province's GRP share of the national total as weights). The weighted geometric mean of the 30 provinces is taken as China's overall level, as shown in Figure 4. Meanwhile, the geometric means of China's GTFP, PTE, SE, and TC are 0.947, 0.971, 0.961, and 1.015, respectively, indicating that industrial GTFP declined by an average of 5.3% annually during the sample period, reflecting a state of regression. This result stems from the opposing effects of technical efficiency change and TC: Despite a 1.5% technological progress that shifts the production frontier outward, the combined losses in pure technical efficiency (2.9%) and SE (3.9%) cause actual output to deviate further from the optimal frontier.

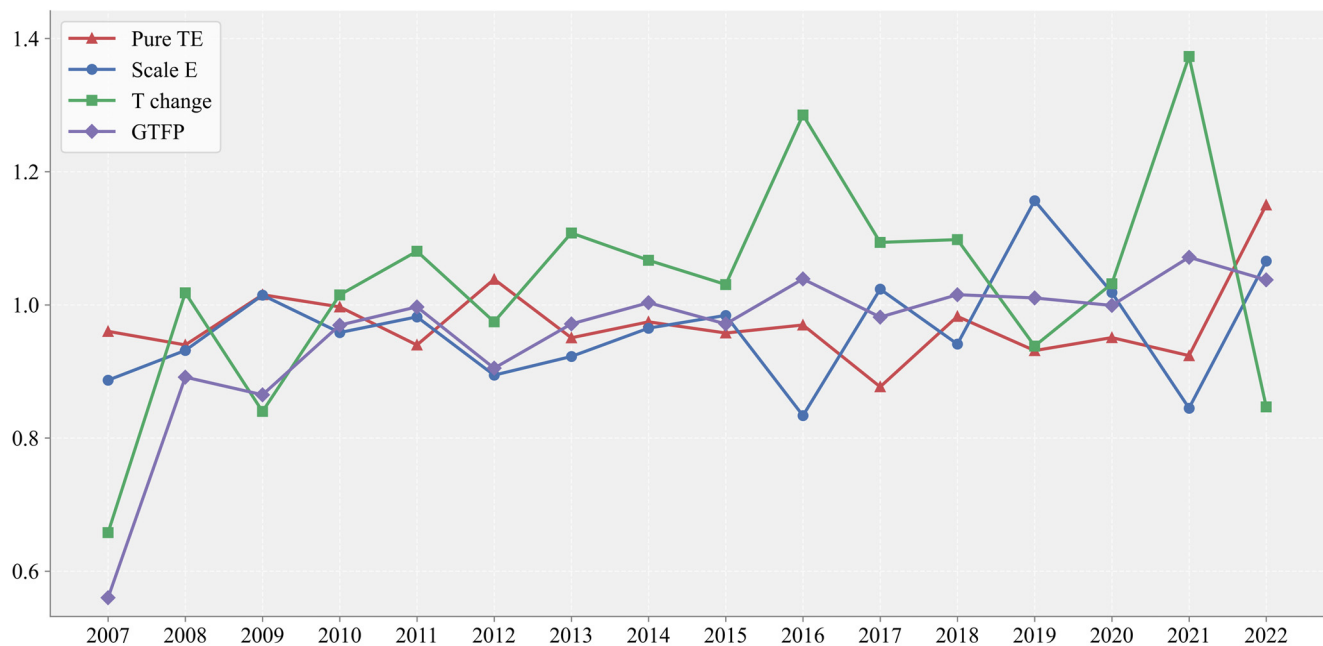


Figure 4. GTFP and its decomposition of China's industrial sectors, 2007–2022. **Note:** E denotes efficiency, T denotes technology.

As shown in Figure 4, China's GTFP and its decomposition factors exhibited significant dynamic fluctuations during 2007–2022, with TC displaying the most dramatic volatility and serving as the core variable driving GTFP variations. From 2007 to 2008, GTFP rapidly rebounded from 0.560 to 0.891, primarily attributable to TC surging from 0.658 to 1.018. This reflects the recovery growth in technology investment under national stimulus policies following the financial crisis. A notable divergence emerged during 2015–2016, when TC reached a phased peak of 1.285, likely associated with green technology breakthroughs driven by supply-side structural reforms and the “Internet Plus” action plan. Meanwhile, SE plummeted to a trough of 0.834, indicating efficiency losses caused by enterprise downsizing under capacity-reduction policies. SE rebounded rapidly to 1.156 during 2018–2019, possibly benefiting from industrial agglomeration effects manifesting under the regional coordinated development strategy. During 2020–2021, TC soared to a historical high of 1.373, likely attributable to the explosive post-pandemic growth of the digital economy and the accelerated application of green technologies under the pressure of China's “dual-carbon” targets. However, TC plunged precipitously to 0.847 in 2022, while PTE climbed countercyclically to 1.150. This divergence suggests that, against the backdrop of technological progress being hindered by external environmental shocks (e.g., recurring pandemic waves and global supply chain restructuring), industrial enterprises enhanced the utilization efficiency of existing technologies through management optimization, process reengineering, and industrial structure adjustment. However, this also exposed the fragility of technological innovation capabilities.

Figure 4 does not depict the correlations between GTFP, PTE, SE, and TC. We use Spearman's rank correlation coefficient to further investigate these relationships, as shown in Table 3. The results demonstrate that GTFP is most closely related to PTE, suggesting it has the strongest effect. The TC index has the second-strongest influence. Notably, no significant correlation is found between GTFP and SE, implying that changes in SE have less apparent effects on GTFP compared with the other two factors.

Table 3. Spearman’s rank correlation coefficients among efficiency indices.

	GTFP	PTE	SE	TC
GTFP	1			
PTE	0.4451 ***	1		
SE	−0.0228	−0.2661 ***	1	
TC	0.2696 ***	−0.2486 ***	−0.4845 ***	1

Note: *** denotes significance at the 1% level.

In addition, the analysis reveals that PTE is negatively correlated with both SE and TC. A negative correlation is also observed between SE and TC. Zhu et al. [34] found that technical efficiency (the product of PTE and SE) is not synchronized with TC. We go further by demonstrating that PTE, SE, and TC are all asynchronous and exhibit mutual exclusivity.

5.3. Regional Heterogeneity

Based on the GTFP, PTE, SE, and TC of industrial sectors across 30 provinces in China, we calculate the average values for the eastern, central, and western regions using the weighted geometric mean (utilizing the GRP proportion of each province within its region as weights). Figure 5 shows the results. The change rates in industrial GTFP for the eastern, central, and western regions are, respectively, 0.945, 0.930, and 0.975. All three regions show change rates of less than 1, indicating a decline in industrial GTFP across the board. The central region shows the fastest decline, followed by the eastern region, with the western region showing the slowest rate of decline. These findings indicate that the eastern coastal area, which enjoys locational advantages for economic development, and the western region, which benefits from preferential economic development policies, are performing relatively better. By contrast, the central region faces a potential risk of development lag. This analysis highlights regional disparities in China’s green industrial development and suggests the need for targeted policies to address the challenges faced by different regions, particularly the central region.

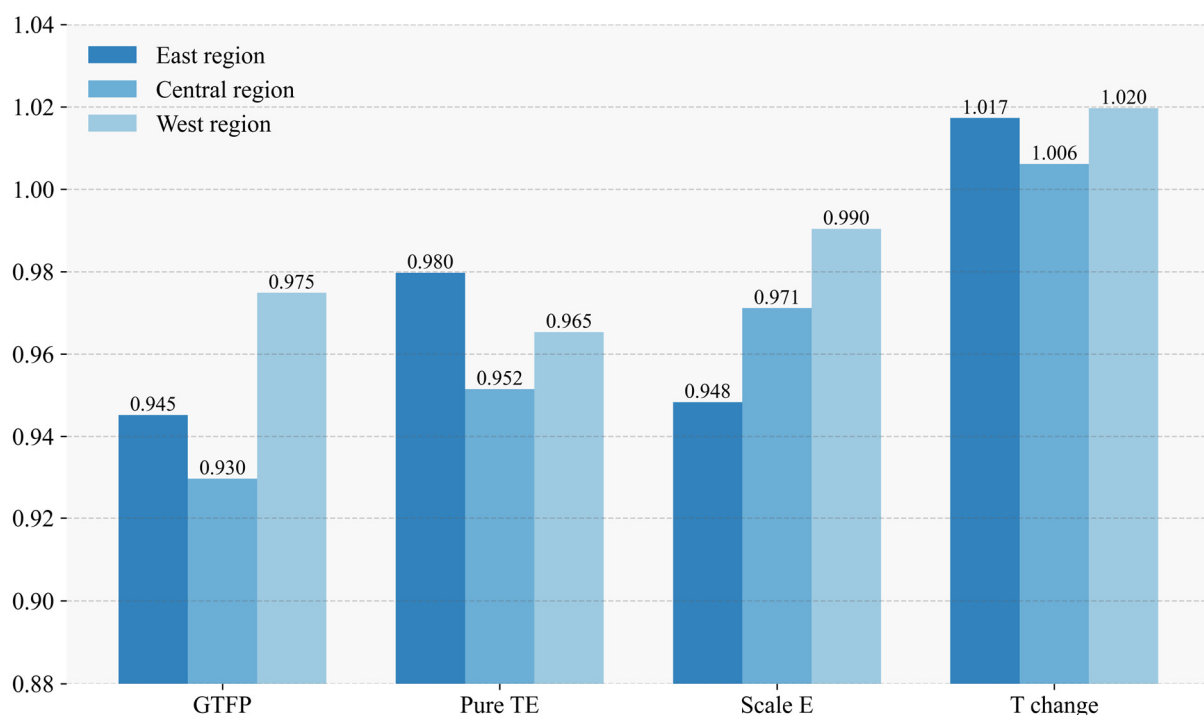


Figure 5. Comparison of the geometric means of four indices across regions, 2006–2022. Note: E denotes efficiency, T denotes technology.

Regarding industrial PTE, the values for the eastern, central, and western regions are, respectively, 0.980, 0.952, and 0.965. This indicates that management standards for industrial sectors in the eastern region surpass those of the western region, which in turn exceed those of the central region. All three regions show signs of inefficient resource allocation, with management levels declining across the board. As for industrial SE, the SE changes in the three regions are all less than 1, indicating that the eastern (0.948), central (0.971), and western (0.990) regions all face the challenge of diminishing returns to scale, albeit with significant differences in the degree of decline. The eastern region exhibits the lowest SE change, rooted in its early industrialization and comprehensive industrial system, where production scale has reached saturation, and the effect of diminishing marginal output is the most pronounced. Meanwhile, it faces multiple bottlenecks—including tight land resources, rising labor costs, and tightening environmental constraints—leading to a continuous decline in the marginal benefits of scale expansion. The central region's SE change is at a moderate level. By absorbing industries transferred from the eastern region, it has achieved rapid scale expansion, with its degree of diminishing returns to scale falling between that of the eastern and western regions. The western region has the highest SE change value, closest to 1, mainly benefiting from its later start in industrialization and lower baseline. Its latecomer advantage enables it to draw on the eastern region's experience to optimize its industrial layout and scale structure, avoiding excessive investment and low-level expansion, thus experiencing a relatively mild degree of diminishing returns to scale.

Regarding the TC index, the western region has the highest value at 1.020, followed by the eastern region at 1.017, while the central region has the lowest value at 1.006. The western region shows the highest TC index, suggesting more technological breakthroughs or the introduction of external technologies. This is mainly attributable to rapid improvements in industrial production technology through the introduction of external technologies and infrastructure development under the support of the Western Development Strategy, especially the rapid growth of certain key industries or emerging sectors. In November 2024, for example, the State Council issued the Catalogue of Encouraged Industries in Western Regions (2025 Edition). This catalog aims to advance the development of industries with local characteristics and comparative advantages in the western region through preferential tax policies and to develop emerging industries in light of local conditions. The eastern region may have entered a relatively mature stage of economic and technological development, where the marginal effects of technological innovation are growing relatively slowly.

To examine whether the differences between regions are significant, we use the Mann–Whitney U statistic and its corresponding *p*-values, as shown in Table 4. The results reveal a significant difference in GTFP between the eastern and central regions, a significant difference between the central and western regions, and no significant difference between the eastern and western regions. In terms of PTE, significant differences exist between the eastern and central regions, as well as between the eastern and western regions, while no dramatic difference is observed between the central and western regions. This, to some extent, suggests that economically developed regions generally possess higher levels of management.

Regarding SE, there are statistically significant differences between the eastern and western regions and between the central and western regions. However, there are no significant differences between the eastern and central regions. As for the TC index, no significant differences are observed among the eastern, central, and western regions. This suggests that, to a certain degree, the eastern region's capacity for technological innovation might have experienced diminishing marginal returns during the study period, while the western region was in a state of technological catch-up. Consequently, the TC indices

across the eastern, central, and western regions appear relatively balanced regarding spatial distribution.

Table 4. Results of the Wilcoxon rank-sum test for four indices.

Null Hypothesis	Mann–Whitney U Statistics	<i>p</i> -Value
GTFP: mean (east) = mean (central)	2.633 ***	0.0085
GTFP: mean (east) = mean (west)	0.567	0.5709
GTFP: mean (central) = mean (west)	−2.070 **	0.0385
PTE: mean (east) = mean (central)	3.009 ***	0.0026
PTE: mean (east) = mean (west)	3.133 ***	0.0017
PTE: mean (central) = mean (west)	−1.088	0.2767
SE: mean (east) = mean (central)	−0.731	0.4646
SE: mean (east) = mean (west)	−2.968 ***	0.0030
SE: mean (central) = mean (west)	−2.218 **	0.0266
TC: mean (east) = mean (central)	0.673	0.5012
TC: mean (east) = mean (west)	1.140	0.2544
TC: mean (central) = mean (west)	0.531	0.5952

Note: ***, ** denote significance at the 1%, 5% levels, respectively.

5.4. Industrial Innovators

A TC value greater than 1 does not necessarily indicate that a province's industrial technology development is in a leading position. This is because an index value exceeding 1 only represents technological progress compared with the previous year for that specific province, and it does not definitively determine the province's current level of industrial technology. Therefore, to identify innovative industrial provinces, in addition to satisfying Equation (10), it is necessary to meet the conditions of Equations (11) and (12). Equation (11) demonstrates that production in time period $t + 1$ occurs outside the production possibility set of period t under VRS, which suggests that the province is expanding beyond the production frontier. Stated differently, using the technology available in period t , the inputs in period $t + 1$ cannot produce the outputs of period $t + 1$. Equation (12) indicates that the province is operating on the production technology frontier. These additional criteria offer a more comprehensive assessment of a province's technological innovation status, considering not only year-on-year progress but also its ability to push beyond existing technological limitations and its position relative to the overall production frontier.

$$TC^{t,t+1} > 1 \quad (10)$$

$$\beta_v^t(z^{t+1}, x^{t+1}, y^{t+1}, b^{t+1}) > 1 \quad (11)$$

$$\beta_v^{t+1}(z^{t+1}, x^{t+1}, y^{t+1}, b^{t+1}) = 1 \quad (12)$$

Table 5 presents the innovative industrial provinces identified through SBM-GMI. Among the 30 provinces, 13 are recorded as innovative industrial provinces: Beijing, Shanghai, Jiangsu, Tianjin, Shandong, Guangdong, Hainan, Hebei, Inner Mongolia, Henan, Zhejiang, Yunnan, and Qinghai. Some provinces maintain their status as industrial innovators for very brief periods, such as Inner Mongolia, Yunnan, and Qinghai. Others, by contrast, consistently remain as industrial innovators throughout most of the study period, notably Shanghai, Beijing, and Jiangsu.

Table 5. List of innovative provinces in China, 2006–2022.

Period	Provinces
2006–2007	Beijing, Shanghai
2007–2008	Beijing, Shanghai, Jiangsu, Zhejiang, Shandong, Guangdong, Hainan
2008–2009	Beijing
2009–2010	Beijing, Hebei, Shanghai, Jiangsu, Shandong, Henan, Guangdong
2010–2011	Beijing, Tianjin, Inner Mongolia, Shanghai, Jiangsu, Zhejiang, Shandong
2011–2012	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Shandong, Hainan
2012–2013	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Shandong, Hainan
2013–2014	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Shandong, Guangdong
2014–2015	Beijing, Tianjin, Hebei, Inner Mongolia, Shanghai, Jiangsu, Shandong, Hainan
2015–2016	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Shandong, Guangdong, Hainan, Qinghai
2016–2017	Beijing, Tianjin, Shanghai, Jiangsu, Shandong, Guangdong, Hainan, Qinghai
2017–2018	Beijing, Shanghai, Jiangsu, Shandong, Guangdong, Hainan, Qinghai
2018–2019	None
2019–2020	Beijing, Shanghai, Jiangsu, Guangdong, Hainan, Yunnan, Qinghai
2020–2021	Beijing, Shanghai, Jiangsu, Guangdong, Hainan
2021–2022	None

We should note that there were “no-innovation provinces” during 2018–2019 and 2021–2022, reflecting the combined effect of the SBM-GMI method’s strict standards for identifying technological innovation and the prevailing macroeconomic environment. First, the 2018–2019 hiatus coincided with the full escalation of China–US trade frictions, impeded access to foreign technology, and domestic deleveraging pressures. Firms’ R&D spending growth slowed; breakthrough innovation in industry declined; the previously prevalent model of technology importation and imitative innovation became unsustainable, and indigenous innovation capacity had not yet reached scale. As a result, expansion of the national production frontier stalled or even contracted, making it difficult for provinces to achieve substantive breakthroughs relative to the frontier. Second, the 2021–2022 hiatus was closely related to repeated COVID-19 shocks to global supply chains, sharp volatility in energy and raw material prices, and deep adjustments in sectors such as real estate. Industrial firms faced the twin squeeze of rising costs and shrinking demand, forcing cuts to innovation investment. Finally, both periods coincided with a transition in the global technological revolution cycle: The dividends from traditional information technologies were fading, while emerging technologies such as artificial intelligence and new energy had yet to translate into large-scale productivity in industry. This produced a plateau in overall technological progress, further increasing the likelihood of “no-innovation provinces.”

6. Conclusions, Implications, and Limitations

6.1. Conclusions

In this study, we first use an SBM model to examine the industrial GDE of China’s 30 provinces from 2006 to 2022. Second, we construct an SBM-GMI model to assess dynamic changes in industrial GTFP for these 30 provinces during the same period, which is then decomposed into PTE, SE, and TC. Third, based on the GTFP, PTE, SE, and TC indices of the 30 provinces, we use the weighted geometric mean to calculate these indices for China as a whole and for its three main regions: eastern, central, and western. Finally, following Oh [38], we identify China’s industrial innovation provinces from 2006 to 2022.

We find the following: (1) The distribution of industrial GDE transformed from a uniform distribution over the course of the 11th and 12th Five-Year-Plan periods into a

pyramid-shaped distribution over the course of the 13th Five-Year-Plan period. (2) China's industrial GTFP continuously declines over the study period, mainly because of decreases in PTE and SE. On the contrary, technological progress shows a positive effect on GTFP. Improvements in PTE contribute the most to GTFP growth, followed by technological progress and, finally, SE. (3) Industrial GTFP faces a central lag risk. The performance of the eastern region in PTE is significantly better than that of the western and central regions. By contrast, the western region shows significantly higher SE than the eastern and central regions. The TC index is relatively balanced across regions. (4) Industrial innovation was not prominent during 2018–2019 and 2021–2022. Shanghai, Beijing, and Jiangsu are consistently at the forefront of China's industrial innovation across multiple periods.

6.2. Policy Implications and Limitations

Based on the classification of provinces according to their performance in terms of PTE, SE, and TC indicators, we make the following policy recommendations. First, the national PTE index of 0.971 is the primary drag on GTFP growth, particularly in Hebei (0.902), Heilongjiang (0.897), Guangxi (0.880), Xinjiang (0.909), and Tianjin (0.920). Key industrial enterprises in these provinces need to establish mentorship relationships with benchmark enterprises in the same industries in frontier PTE provinces to diagnose and transform their production processes, energy management, and environmental governance systems. Meanwhile, a performance-linked reward mechanism for PTE improvement should be established. Here, partial refunds of environmental taxes are directly linked to improvements in enterprise resource productivity (e.g., energy and water consumption per unit of output value), thereby incentivizing enterprises to tap into the resource utilization potential of existing technologies.

Second, the national SE index of 0.961 indicates that differentiated scale-efficiency improvement policies should be implemented for provinces significantly below the national average—such as Qinghai (0.916), Jiangsu (0.924), and Guangdong (0.933). Qinghai's economy is dominated by resource-based industries (salt lake chemicals and nonferrous metals) with short industrial chains and low agglomeration, where enterprises are generally small-scale. It is necessary to promote characteristic industries such as salt lake chemicals and new energy through an “enterprise alliance + shared facilities” model to jointly construct infrastructure, including combined heat and power generation and wastewater treatment facilities. Some regions in Jiangsu face homogeneous industrial competition and scattered industrial park layouts. This requires provincial-level coordination to guide adjacent parks to form complementary closed loops, thereby reducing redundant construction and logistics losses. In Guangdong, while industries are highly concentrated in the Pearl River Delta [47], the eastern, western, and northern regions have weak industrial foundations with insufficient interregional industrial linkages. It is necessary to guide the transfer of certain segments from the Pearl River Delta to the eastern, western, and northern regions, forming a provincially collaborative green industrial chain.

Third, although the national TC index is 1.015, provinces such as Yunnan (0.957), Heilongjiang (0.991), and Hebei (0.990) have experienced technological frontier regression. It is necessary to establish a “technology demand–supply” matching platform led by the central government or industry associations. This would encourage regions with high TC (e.g., Beijing at 1.110) to transfer mature technologies, while regions with low TC compile demand lists. Priority project approval support should be provided for successfully matched and implemented green technology transfer projects. Preferential tax policies should be granted to enterprises that purchase and apply certified advanced green technologies that significantly improve their energy efficiency or emission reduction levels.

This study has two main limitations. First, owing to constraints in the industrial CO₂ data from CEADs, the research period extends only to 2022. Future studies should track dynamic changes in China's industrial GTFP in more recent years. Second, although this study identifies a “central collapse” phenomenon in China's GTFP, it does not investigate whether this collapse is attributable to the “pollution haven” hypothesis—where inefficient industries migrate from the east to the central region—or to specific failures in regional investment strategies. Future research should employ econometric methods to investigate the specific causes of this phenomenon.

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Abbreviations

The following abbreviations are used in this manuscript:

CEADs	Carbon Emission Accounts and Datasets
COD	Chemical Oxygen Demand
CRS	Constant Returns to Scale
DDF	Directional Distance Function
DEA	Data Envelopment Analysis
DMU	Decision-Making Units
GDE	Green Development Efficiency
GMI	Global Malmquist Index
GRP	Gross Regional Product
GTFP	Green Total-Factor Productivity
PTE	Pure Technical Efficiency
SBM	Slacks-Based Measure
SE	Scale Efficiency
SO ₂	Sulfur Dioxide
TC	Technological Change
VRS	Variable Returns to Scale

Appendix A

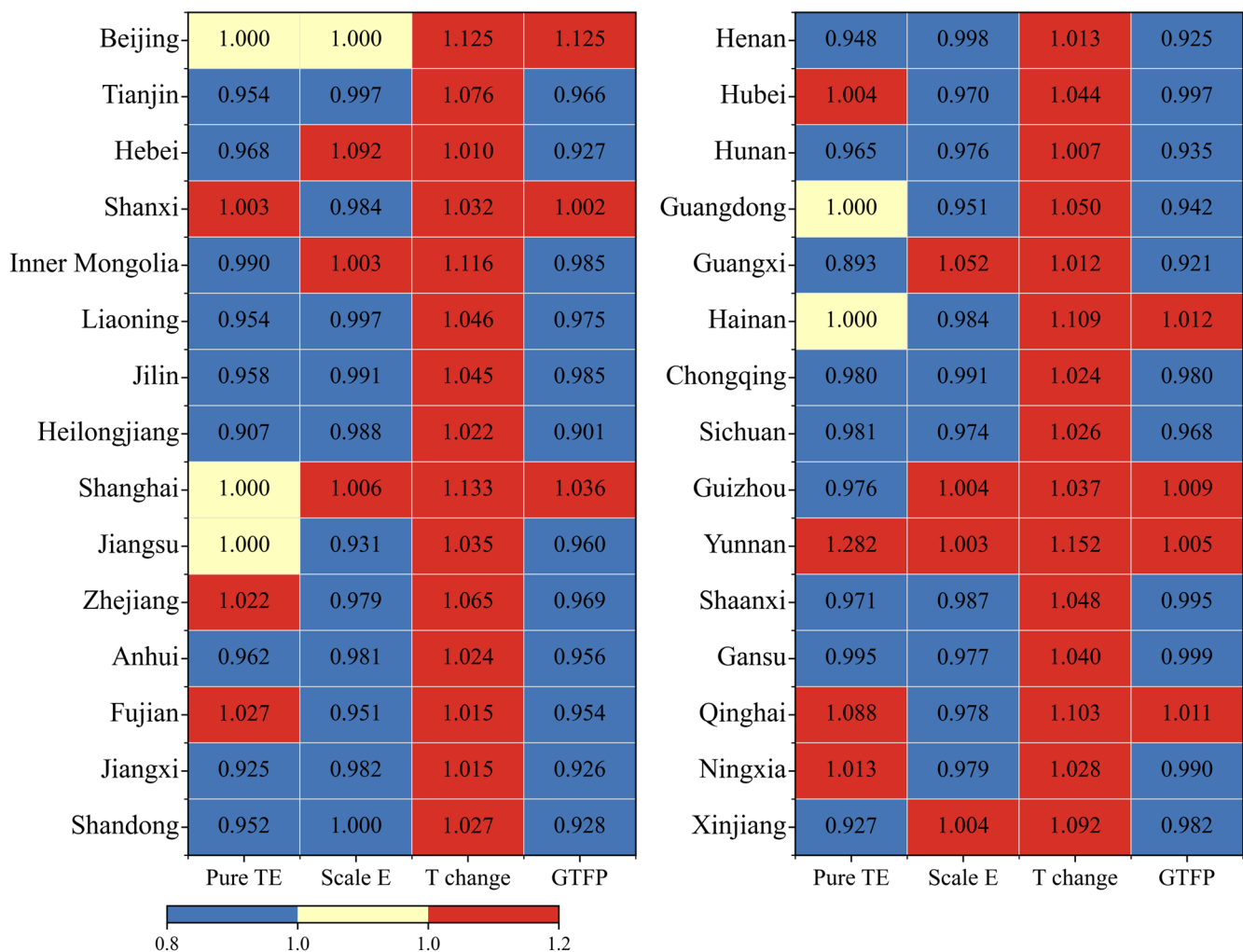


Figure A1. Arithmetic mean of GTFP and its decomposition across 30 provinces. **Note:** E denotes efficiency, T denotes technology.

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