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# THE IMPACT OF NEW ENERGY SOURCES ON INDUSTRIAL GREEN TOTAL FACTOR PRODUCTIVITY

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Abstract. The green and low-carbon transformation of the energy sector is the critical pathway to achieving China's "carbon peak and carbon neutrality" goals. Although considerable progress has been made in separate studies on the new energy industry and Green Total Factor Productivity (GTFP), research exploring their relationship, especially at the industrial level, remains scarce. Based on panel data of 30 Chinese provinces from 2013 to 2023, this study proposes the Convexificated Support Vector Frontiers-Malmquist method, a novel approach based on structural risk minimization, to measure industrial GTFP. The entropy weight method is employed to construct composite scores for three sub-systems of the new energy industry: innovation, coordination, and greenness (foundation). A two-way fixed effects model is then applied to examine the impact of these sub-systems on industrial GTFP. The empirical results demonstrate that New Energy Industry Innovation (NEII) and Coordination of New Energy Industry (CNEI) significantly promote industrial GTFP, with coefficients of 0.4530 and 0.5088 respectively, both significant at the 1% level. In contrast, the New Energy Industry Foundation (NEIF) does not exhibit a statistically significant effect. These findings remain robust across endogeneity tests using the two-stage least squares (2SLS) method with lagged instrumental variables, as well as robustness checks including Winsorization and exclusion of pandemic-affected samples. The study contributes to the literature by introducing the CSVF–Malmquist model with superior generalization ability and frontier estimation accuracy, and by providing empirical evidence that innovation capacity and supply-demand coordination in the new energy sector are key drivers of industrial green productivity improvement in China.

**Keywords.** New energy industry, Green total factor productivity (GTFP), CSVF-Malmquist model, Two-way fixed effects, Entropy weight method, Carbon Peak and Carbon Neutrality.



## 1. Introduction

The *Outline of the 14th Five-Year Plan for National Economic and Social Development and the Long-Range Objectives Through 2035 of the People's Republic of China* explicitly proposes building a modern energy system, advancing the energy revolution, and constructing a clean, low-carbon, safe, and efficient energy system to enhance energy supply security. Since energy activities are the primary source of carbon emissions, the green and low-carbon transformation of the energy sector is the critical pathway to achieving the "carbon peak and carbon neutrality" goals. Under the guidance of this national strategy, China's new energy industry has achieved remarkable progress, with non-fossil energy experiencing leapfrog development.

China has adhered to the parallel development of centralized and distributed energy systems, accelerating the construction of large-scale wind power and photovoltaic (PV) bases. As of the end of August 2025, the cumulative installed capacity of wind power and PV generation exceeded 1.69 billion kilowatts, more than tripling the 2020 level, contributing approximately 80% of the nation's newly added

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power generation capacity over the past five years. The share of non-fossil energy in total energy consumption increased from 16.0% in 2020 to 19.8% in 2024, rising by nearly 1 percentage point annually, while the share of wind and PV power generation in total national electricity output increased by an average of 2.2 percentage points per year.

The multi-energy complementary system has also become increasingly sophisticated. China has continued to advance the construction of hydropower bases in the southwest, while steadily and safely developing coastal nuclear power. As of the end of August 2025, the installed capacity of conventional hydropower reached approximately 380 million kilowatts, and nuclear power installed capacity reached 125 million kilowatts, both ranking first in the world. Demonstration applications of biomass energy, geothermal energy, ocean energy, and green hydrogen have also been advancing in an orderly manner with positive results.

The regulatory capacity of the energy system has been continuously strengthened. To accommodate the large-scale grid integration of new energy sources, China has accelerated the construction of a new-type power system and promoted the flexibility retrofitting of coal-fired power units. Currently, over 50% of coal-fired units have achieved deep peak-shaving capability. The new energy storage industry has developed rapidly; by the end of 2024, the installed capacity of new-type energy storage reached 73.76 million kilowatts—20 times that of 2020—accounting for over 40% of the global total.

Thanks to these developments, China's energy structure has been continuously optimized. The share of fossil energy in total energy consumption declined from 84.0% in 2020 to 80.2% in 2024. According to relevant plans, by 2030, non-fossil energy is expected to account for 50% of total electricity generation, with total energy consumption controlled within 6 billion tonnes of standard coal equivalent. At present, the new energy industry has become a core pillar supporting China's energy security, response to global climate change, and pursuit of high-quality development. (Data sources: National Development and Reform Commission, *Strategy for Energy Production and Consumption Revolution*; State Council Information Office, *China's Actions on Carbon Peak and Carbon Neutrality* White Paper.)

Existing research on the new energy industry includes the following contributions. Wang [24] constructed an evaluation index system for the high-quality development of China's new energy industry, noting that the overall level exhibits a fluctuating upward trend. The study further identified an "anti-Matthew effect," with inter-provincial disparities narrowing over time. Human capital and financial support are important factors promoting high-quality development of China's new energy industry, while exchange rate volatility and import tariffs tend to inhibit it. Wang [25] pointed out that vigorously developing new energy is an inevitable choice for improving China's energy structure, ensuring national energy security, and realizing the vision of carbon peak and carbon neutrality. The development of new energy technologies and the construction of industrial chains can effectively drive the growth of related industries such as equipment manufacturing, scientific research and development, and supporting services, thereby promoting technological innovation and industrial upgrading, cultivating new economic growth points, and holding significant implications for accelerating the optimization and upgrading of China's industrial structure and enhancing comprehensive economic competitiveness. Zhang [34] argued that the new energy industry, characterized by green GDP, high technological content, and broad market prospects, is a key area for promoting industrial structure optimization and upgrading and cultivating new economic growth points. Wang [26] proposed strengthening regional collaboration and economic linkages to strike a balance between energy conservation, emission reduction, and economic growth, thereby promoting the sustainable development of low-carbon cities. Chen [6] contended that although China's industrial sector as a whole has shifted toward technology-driven growth, high-energy-consuming industries still need to improve energy-efficiency technologies to achieve fully sustainable development.

Data Envelopment Analysis (DEA) is a non-parametric evaluation method first proposed by Charnes, Cooper, and Rhodes [4] from the United States. It is often used to evaluate the relative efficiency of

DMUs with multiple input and output factors. DEA is a non-parametric method of linear programming, which has developed rapidly and been widely applied. The DEA method does not require pre-specification of the specific form of the production function nor pre-assumption of the distribution of inefficiency terms. The evolution of Total Factor Productivity (TFP) indices based on the DEA method is as follows: (1) TFP indices based on current-period DEA, including Malmquist productivity index, Luenberger productivity index, and Malmquist-Luenberger productivity index. Färe et al. [10], based on the constant returns to scale CCR model, used the Malmquist index method to decompose total factor productivity into technological progress and technical efficiency improvement. Chambers et al. [3] proposed the Luenberger index method, further decomposing the total factor productivity growth rate into three components: technological progress rate, technical efficiency change, and scale efficiency change. Chung et al. [8] proposed the Malmquist-Luenberger productivity index method, decomposing technological progress and technical efficiency from total factor productivity. Thanassoulis et al. [21] constructed a cost Malmquist index model using price information of input factors, and the index was decomposed to explain differences in technical and cost production efficiency. Long [14] evaluated the eco-efficiency and effectiveness of sustainable urban development in 35 major Chinese cities from 2011 to 2015 using a super-efficiency SBM–DEA model with undesirable outputs and the Malmquist–Luenberger index, and further integrated urban HDI and life satisfaction to measure development effectiveness. Liang and Zhang [15] proposed modified radial Malmquist–Luenberger index models to address the infeasibility problem in productivity measurement with undesirable outputs and applied them to evaluate the productivity changes of 28 Chinese banks from 2007 to 2016. Yang and Huang [31] assessed the mining eco-efficiency of 27 Chinese provinces from 2008 to 2018 by integrating an undesirable output SBM-DEA model and the Malmquist-Luenberger index, revealing overall improvement with significant spatial disparities and identifying the impact of non-desired outputs like carbon emissions and violation cases. Lacka and Brzezicki [12] used the non-radial SBM model and Malmquist index to evaluate the efficiency and productivity of National Innovation Systems in 27 European countries from 2012 to 2019, finding that newer EU members often achieved higher efficiency despite having smaller innovation inputs. Zhu et al. [36] constructed a Global Malmquist-Luenberger index based on a novel production technology that considers the weak disposability between energy inputs and $CO_2$ emissions to measure and decompose the total factor carbon emission productivity of 41 industrial sectors in China from 2013 to 2016. Jebali and Essid [11] employed the Malmquist–Luenberger productivity index to evaluate and decompose the total factor environmental productivity of Mediterranean countries from 2009 to 2014, finding an overall negative developmental trend primarily driven by technological change rather than efficiency gains.

(2) TFP index extensions, such as TFP productivity indices of sequential DEA, global DEA-based TFP productivity indices, window DEA-based TFP productivity indices, and TFP productivity indices of intertemporal DEA. Shestalova [20] introduced a sequential Malmquist productivity index, which constructs the best-practice production technology frontier by utilizing the production technology set defined by current and past observations of DMUs. The decomposition of this index resembles that of the conventional Malmquist index, differing only in the reference production frontier. Since sequential DEA assumes that no period's technology is superior to others, Pastor and Lovell [19] put forward the idea of building a production technology set comprising data from all periods of all DMUs as a global benchmark to compute the Global-Malmquist productivity index. The fundamental concept behind window DEA is to segment the study period into several windows of a fixed width, treating the same DMU in different windows as distinct entities, thereby effectively increasing the number of DMUs. A drawback of this approach, however, is that it may lead to low discrimination in relative efficiency [28]. Productivity measurement often presupposes that all evaluated units share the same technological level—that is, they operate on a common production frontier. In reality, however, heterogeneity arises due to differences in internal characteristics or external environments among the units being evaluated

[7]. Chen et al. [5] used a sequential DEA model to compare the efficiency of the urban water sectors in China and major OECD countries from 1998 to 2017, and analyzed the impact of factors such as capital deepening and water stress on efficiency. Liu and Huang [17] applied a virtual frontier DEA model and Malmquist productivity index to measure and decompose the efficiency of China's high-tech industry across 29 provinces from 2011 to 2015, addressing the issue of tied ranks among efficient DMUs and analyzing the drivers of productivity change. Wang et al. [27] proposed a global DEA-Malmquist productivity index to measure the bias of technical change in China's industrial energy and environmental productivity, and identified labor, energy consumption, and $CO_2$ emissions as the main drivers of technological progress through empirical analysis. Brzezicki [2] systematically reviewed the origin, evolution, and various methodological extensions of the Malmquist Productivity Index based on Data Envelopment Analysis, categorizing its developments into adaptations from DEA, novel MPI frameworks, and integrations with other dynamic analysis methods. Mitropoulos [18] employed a two-stage network DEA model and Malmquist index to evaluate the trade-off between production efficiency and service quality in EU healthcare systems during the 2009–2013 economic crisis, revealing that efficiency gains were often achieved at the expense of patient satisfaction and safety. Shen and Wang [35] used a spatial econometric model to analyze the inverted U-shaped impact of forestry industry total factor productivity on $CO_2$ emissions in China, revealing significant spatial spillover effects and regional heterogeneity.

(3) Extension of TFP indices based on DEA. The HMB index considers input and output directions and does not require a choice between input and output directions. Under constant or variable returns to scale, the HMB index retains the characteristics of total factor productivity, and the strong disposability of inputs and outputs enables it to satisfy the decisive axiom, avoiding the problem of no feasible solution [1]. The Malmquist index method constructs the TFP index using geometric weighting. Yin and Duan [33] drew on the idea of Malmquist but used arithmetic weighting to derive the efficiency allocation equation in order to decompose total factor productivity, technological progress, etc., into corresponding factor efficiencies, and conducted an empirical analysis using Chinese provincial data. Ding and Dong [9] employed the HMB index, Theil index, kernel density estimation, and Markov chain analysis to measure and examine the spatiotemporal evolution of green total factor productivity in China's sports industry (2013–2022), revealing an overall wave-like upward trend driven mainly by pure technical efficiency, significant regional disparities with the eastern region leading in growth, and strong state-dependence with limited cross-level transitions. Yang and Meseretchanie [30] used a dynamic panel model and HMB index to analyze the mediating role of farmland transfer in the impact of digital financial inclusion on agricultural total factor productivity in China, finding that digital finance promotes productivity primarily through improved scale and allocation efficiency.

The Malmquist model for analyzing productivity changes is a theoretical extension of the super-efficiency DEA model. One of its drawbacks is the problem of no feasible solution under the assumption of variable returns to scale.

Regarding research on Green Total Factor Productivity (GTFP), scholars have explored the topic from multiple industries and perspectives. Early studies, such as Yang [32], applied total factor productivity theory to the postal and telecommunications industry, using the Malmquist index to analyze productivity changes in China's postal and telecommunications sector, and discussed key factors affecting the industry from both macro and micro comparative perspectives. Subsequently, research gradually expanded to logistics, industry, and other fields. For instance, Liang [16] adopted GTFP as an important indicator for measuring the high-quality development of regional economies, assessing the green development level of the logistics industry in the context of Beijing-Tianjin-Hebei integration, with the aim of providing a basis for optimized resource allocation and low-carbon transformation. Meanwhile, Wang [23] analyzed China's GTFP from 1999 to 2012 and found that the average growth rate was 1.33%, with energy conservation and emission reduction performance making outstanding contributions, particularly with $SO_2$ emission reductions outperforming COD reductions.

Some research findings have emerged at the intersection of the new energy industry and GTFP. Li [13], based on panel data from 282 prefecture-level cities in China and using a PSM-DID model, found that the construction of new energy demonstration cities significantly enhanced urban GTFP. Xie [29] further supported this conclusion, noting that the pilot policy of new energy demonstration cities primarily improves GTFP by driving substantive green technological innovation, with industrial structure optimization playing a positive moderating role. The policy effects are stronger in central and western regions, non-resource-based cities, and cities with stronger environmental regulations.

In summary, while considerable achievements have been made in research on either the new energy industry or GTFP, studies exploring the relationship between the two remain relatively scarce. Although some research has examined the connection between the new energy industry and GTFP, virtually no study has specifically analyzed the relationship between the new energy industry and *industrial* GTFP. In light of this, the present study draws on data from 30 Chinese provinces covering the period 2013–2023 (due to data unavailability, Tibet and the Hong Kong, Macao, and Taiwan regions are excluded). It employs the CSVF–Malmquist method proposed herein to measure industrial GTFP, uses the entropy weight method to calculate scores for three sub-systems of the new energy industry—innovation, coordination, and greenness—and adopts a two-way fixed effects model to analyze their impact on industrial GTFP.

This paper is organized as follows. In Section 2, the research methodology and data description are provided, including the CSVF–Malmquist model, the regression model, variable selection and measurement, and data sources. Section 3 presents the empirical analysis. The paper is concluded in Section 4.

## 2. Research Methodology and Data Description

The rest of the study is unfolded as follows. In Section 2, the CSVF–Malmquist method is employed to measure industrial green total factor productivity, while the entropy weight method is used to calculate composite scores for the three sub-systems of the new energy industry: innovation, coordination, and greenness. In Section 3, a two-way fixed effects model is applied to examine the effects of new energy industry innovation, coordination, and greenness on industrial GTFP. The paper is concluded in Section 4.

### 2.1. **Research methods.**

2.1.1. *The CSVF–Malmquist model.* Based on the work of Valero-Carreras [22], this paper proposes a novel method for measuring green total factor productivity. The SVF model presented therein is as follows:

$$
\begin{aligned}
\min_{w,\xi_i} \quad & \|w\|_1 + C\sum_{i=1}^{n}\xi_i \\
\text{s.t.} \quad & y_i - w\phi^G_{SVF}(x_i) \le 0, \quad i=1,\dots,n \\
& w\phi^G_{SVF}(x_i) - y_i \le \varepsilon + \xi_i, \quad i=1,\dots,n \\
& W_{l_1 l_2 \cdots s_j \cdots l_m} \le W_{l_1 l_2 \cdots l_m}, \quad \forall l_1,\dots,l_m, \quad \forall s_j = l_j - 1, \quad \forall j = 1,\dots,m \\
& \xi_i \ge 0, \quad i=1,\dots,n
\end{aligned}
\tag{2.1}
$$

Then, the CSVF model:

TABLE 1. Symbols for Model (2.1)

| *Symbol* | *Meaning* |
|---|---|
| $n$ | The number of Decision Making Units (DMUs) in the learning sample (training set). |
| $m$ | The dimensionality of the input variables. |
| $x_i = (x_i^{(1)}, \dots, x_i^{(m)}) \in \mathbb{R}_+^m$ | The input vector of the $i$-th DMU, where $x_i^{(j)}$ denotes the value of the $i$-th DMU on the $j$-th input dimension. |
| $y_i \in \mathbb{R}_+$ | The actual output value of the $i$-th DMU (single-output case). |
| $G$ | A grid defined on the input space $\mathbb{R}_+^m$. For each input dimension $j$ ($j = 1, \dots, m$), there are $k_j$ knots $0 < t_1^{(j)} < t_2^{(j)} < \cdots < t_{k_j}^{(j)}$, partitioning that dimension into $k_j$ intervals. |
| $C_{l_1 \dots l_m}$ | The unique cell in grid $G$ indexed by $(l_1, \dots, l_m)$, defined as $C_{l_1 \dots l_m} = \{x \in \mathbb{R}_+^m : t_{l_j}^{(j)} \le x^{(j)} < t_{l_j+1}^{(j)},\ j = 1, \dots, m\}$. |
| $a_{l_1 \dots l_m}$ | The lower extreme knot-point of cell $C_{l_1 \dots l_m}$, i.e. $a_{l_1 \dots l_m} = (t_{l_1}^{(1)}, \dots, t_{l_m}^{(m)})$. |
| $b_{l_1 \dots l_m}$ | The upper extreme knot-point of cell $C_{l_1 \dots l_m}$, i.e. $b_{l_1 \dots l_m} = (t_{l_1+1}^{(1)}, \dots, t_{l_m+1}^{(m)})$. |
| $d$ | The number of cells per input dimension, which determines the granularity of grid $G$. |
| $B(x^{(j)} - t_{l_j}^{(j)})$ | A binary activation function: value 1 when $x^{(j)} \ge t_{l_j}^{(j)}$, and 0 otherwise. |
| $L_{l_1 \dots l_m}(x)$ | The activation function for cell $C_{l_1 \dots l_m}$, defined as $L_{l_1 \dots l_m}(x) = \prod_{j=1}^m B(x^{(j)} - t_{l_j}^{(j)})$. |
| $\phi_{SVF}^G(x)$ | The SVF transformation function, mapping input vector $x$ to a binary vector. Dimension is $q = k_1 \cdot k_2 \cdots k_m$. |
| $w$ | The parameter vector of dimension $q = k_1 \cdot k_2 \cdots k_m$. Each component $w_{l_1 \dots l_m} \in \mathbb{R}$ corresponds to a cell in grid $G$. |
| $\xi_i \quad (i = 1, \dots, n)$ | Non-negative slack variables measuring the empirical error of the $i$-th DMU. |
| $W_{l_1 l_2 \dots l_m}$ | The cumulative weight, defined as $W_{l_1 \dots l_m} := \sum_{s_1=1}^{l_1} \cdots \sum_{s_m=1}^{l_m} w_{s_1 \dots s_m}$. |
| $\lVert w \rVert_1$ | The L1 norm of the parameter vector. |
| $C \in \mathbb{R}_+$ | The regularization parameter, balancing the regularization term and the empirical error term. |
| $\varepsilon \in \mathbb{R}_+$ | The $\varepsilon$-insensitive margin, defining upper and lower "correcting surfaces". |

$$\hat{T}_{CSVF} = \left\{ (x, y) \in \mathbb{R}_+^{m+1} : \begin{array}{l} y \le \displaystyle\sum_{\substack{l_1 = 1, \dots, k_1 \\ \vdots \\ l_m = 1, \dots, k_m}} \lambda_{l_1 \dots l_m} \hat{f}_{SVF}(a_{l_1 \dots l_m}) \\ x^{(j)} \ge \displaystyle\sum_{\substack{l_1 = 1, \dots, k_1 \\ \vdots \\ l_m = 1, \dots, k_m}} \lambda_{l_1 \dots l_m} a_{l_1 \dots l_m}^{(j)}, \quad \forall\, j = 1, \dots, m \\ \displaystyle\sum_{\substack{l_1 = 1, \dots, k_1 \\ \vdots \\ l_m = 1, \dots, k_m}} \lambda_{l_1 \dots l_m} = 1 \\ \lambda_{l_1 \dots l_m} \ge 0, \quad \forall\, l_1, \dots, \forall\, l_m \end{array} \right\} \tag{2.2}$$

TABLE 2. Symbols for Model (2.2)

| *Symbol* | *Meaning* |
|---|---|
| $\hat{T}_{CSVF}$ | The convexified production possibility set, satisfying the convexity assumption. |
| $(x, y) \in \mathbb{R}_+^{m+1}$ | The input–output combination to be tested for membership in the production possibility set. |
| $a_{l_1 \ldots l_m} = (t_{l_1}^{(1)}, \ldots, t_{l_m}^{(m)})$ | The lower extreme knot-point of cell $C_{l_1 \ldots l_m}$ in the grid. |
| $a_{l_1 \ldots l_m}^{(j)}$ | The $j$-th input-dimension component of the lower extreme knot-point $a_{l_1 \ldots l_m}$. |
| $\hat{f}_{SVF}(a_{l_1 \ldots l_m})$ | The value of the Model (2.1) step-function estimate at the point $a_{l_1 \ldots l_m}$. |
| $\lambda_{l_1 \ldots l_m} \geq 0$ | Convex combination weights (intensity variables). |
| $\sum \lambda_{l_1 \ldots l_m} = 1$ | The convexity constraint, corresponding to the Variable Returns to Scale (VRS) assumption. |

TABLE 3. Symbols for Model (2.3)

| *Symbol* | *Meaning* |
|---|---|
| $K$ | Total number of grid cells $= d^m$ ($d$ partitions, $m$ input dimensions) |
| $\mathbf{a}_k$ | Lower-left vertex of the $k$-th cell (input vector) |
| $\hat{f}_{\mathrm{SVF}}(\mathbf{a}_k)$ | Estimated output at that vertex |
| $\lambda_k$ | Convex-combination weight of the $k$-th extreme point |

Based on the above model, we propose the CSVF-Malmquist model. Compared with previous models, this model is constructed based on structural risk minimization, exhibiting better generalization ability, stronger robustness, and more accurate frontier estimation. It can significantly reduce bias and MSE. The model is as follows:

$D^t(\mathbf{x}_i^t, y_i^t)$: evaluate period $t$ against its own period-$t$ frontier.

$$
\begin{aligned}
D^t(\mathbf{x}_i^t, y_i^t) = \max_{\phi, \boldsymbol{\lambda}} \ & \phi \\
\text{s.t.} \quad & \sum_{k=1}^{K} \lambda_k a_k^{(j)} \leq x_i^{t(j)}, \\
& \sum_{k=1}^{K} \lambda_k \, \hat{f}^{\,t}(\mathbf{a}_k) \geq \phi \cdot y_i^t, \\
& \sum_{k=1}^{K} \lambda_k = 1, \\
& \lambda_k \geq 0, \quad j = 1, \ldots, m, \quad i = 1, \ldots, n
\end{aligned} \tag{2.3}
$$

After calculating the data for different periods, the Malmquist model can be used to calculate GTFP. The model is as follows:

$$
\begin{aligned}
\mathrm{EFFCH}_i &= \frac{D^{t+1}(\mathbf{x}_i^{t+1}, y_i^{t+1})}{D^t(\mathbf{x}_i^t, y_i^t)}, \\
\mathrm{TECH}_i &= \sqrt{\frac{D^t(\mathbf{x}_i^{t+1}, y_i^{t+1})}{D^{t+1}(\mathbf{x}_i^{t+1}, y_i^{t+1})} \times \frac{D^t(\mathbf{x}_i^t, y_i^t)}{D^{t+1}(\mathbf{x}_i^t, y_i^t)}}, \\
\mathrm{TFPCH}_i = \mathrm{EFFCH}_i \times \mathrm{TECH}_i &= \sqrt{\frac{D^t(\mathbf{x}_i^{t+1}, y_i^{t+1})}{D^{t+1}(\mathbf{x}_i^{t+1}, y_i^{t+1})} \times \frac{D^t(\mathbf{x}_i^t, y_i^t)}{D^{t+1}(\mathbf{x}_i^t, y_i^t)}}
\end{aligned} \tag{2.4}
$$

TABLE 4. Symbols for Model (2.5)

| *Symbol* | *Meaning* |
|---|---|
| $\mathrm{GTFP}_{it}$ | Green Total Factor Productivity of the Industrial sector |
| $\mathrm{NEII}_{it}$ | New Energy Industry Innovation |
| $\mathrm{CNEI}_{it}$ | Coordination of New Energy Industry |
| $\mathrm{NEIF}_{it}$ | New Energy Industry Foundation |
| $\mathrm{IA}_{it}$ | Industrial Agglomeration |
| $\mathrm{OU}_{it}$ | Level of Opening-up |
| $\mathrm{ER}_{it}$ | Environmental Regulation |
| $\mathrm{GI}_{it}$ | Government Intervention |
| $i$ | Province |
| $t$ | Year |
| $\alpha_i$ | Individual Fixed Effect |
| $\gamma_t$ | Time Fixed Effect |
| $\beta_1, \beta_2, \beta_3$ | Coefficients of new energy industry-related variables |
| $\delta_1, \delta_2, \delta_3, \delta_4$ | Coefficients of core explanatory variables |
| $\varepsilon_{it}$ | Random Disturbance Term |

TABLE 5. Input–Output Indicator System

| *Primary Indicator* | *Secondary Indicator* | *Meaning* | *Unit* |
|---|---|---|---|
| Input | Capital Input | Fixed asset investment in the industrial sector | 100 million yuan |
| | Energy Input | Industrial electricity consumption | 100 million kWh |
| | Labor Input | Employment in the industrial sector | 10,000 persons |
| Output | Desirable Output | Industrial output value | 100 million yuan |
| | Undesirable Output | Pollution discharge fee | 100 million yuan |

In our study, for simplicity, we set each grid to a uniform width, as testing all hyperparameter combinations would be computationally prohibitive. We arbitrarily assigned the following values to each hyperparameter: $C \in \{0.1, 0.5, 1, 2, 5\}$, $\varepsilon \in \{0, 0.001, 0.01, 0.1, 0.2\}$, $d \in \{3, 6, 9, 12, 15\}$.

2.1.2. *The regression model.* In this section, a two-way fixed effects model is used. The model is as follows:

$$GTFP_{it} = \alpha_i + \gamma_t + \beta_1 NEII_{it} + \beta_2 CNEI_{it} + \beta_3 NEIF_{it} + \delta_1 IA_{it} + \delta_2 OU_{it} + \delta_3 ER_{it} + \delta_4 GI_{it} + \varepsilon_{it} \quad (2.5)$$

### 2.2. **Variable selection and measurement.**

2.2.1. *Dependent variable.* This paper selects the GTFP of the industrial sector as the dependent variable, and the measurement methods use Model (2.3) and Model (2.4). $TFPCH_i$ represents the changes in green total factor productivity. The index calculated by this method represents the change rate of GTFP in the measured province relative to the previous year and cannot directly reflect the overall change in GTFP. Therefore, assuming that the GTFP value in the first year of the study period, 2013, is 1, the GTFP value in subsequent years is equal to the GTFP value of the previous year multiplied by the Malmquist index of the current year. Panel data of GTFP are obtained using the cumulative method. This paper constructs the input-output indicator system of green total factor productivity for 30 provinces in China from 2013 to 2023, as shown in Table 5.

Fixed asset investment is deflated to 2013 constant prices using the fixed asset investment price index; where this index is unavailable, the CPI is used as a substitute. Output is defined as each province's industrial output value minus pollution discharge fee, deflated to 2013 constant prices using the PPI. The output indicators are consolidated into a single output by subtracting the pollution discharge fee from the industrial output value.

TABLE 6. New Energy Industry Indicator System

| *Primary Indicator* | *Secondary Indicator* | *Tertiary Indicator* | *Description* | *Dir.* |
|---|---|---|---|---|
| NEII | Innovation Input | Capital Input | R&D expenditure (10,000 yuan) | + |
| | | Human Capital Input | Full-time equivalent of R&D personnel (persons) | + |
| CNEI | Energy Supply and Demand | Electricity Demand | Total electricity consumption (100 million kWh) | + |
| | | New Energy Power Generation | New energy power generation (10,000 kWh) | + |
| | | Coal Supply | Coal production (10,000 tons) | − |
| | | Petroleum Supply | Oil supply (10,000 tons) | − |
| NEIF | Circulation Capacity | Railway Mileage | Railway operating mileage (10,000 km) | + |
| | | Highway Mileage | Highway mileage (10,000 km) | + |
| | Communication Infra. | Optical Cable Length | Long-distance optical cable route length (10,000 km) | + |
| | | Mobile Phone Facility | Mobile telephone exchange capacity (10,000 sub.) | + |

TABLE 7. Descriptive Statistics

| *Variable* | *N* | *Mean* | *Std.Dev.* | *Min* | *P25* | *Median* | *P75* | *Max* |
|---|---|---|---|---|---|---|---|---|
| GTFP | 300 | 0.9487 | 0.1157 | 0.6443 | 0.8916 | 0.9709 | 1.0151 | 1.3776 |
| NEII | 300 | 0.1925 | 0.2521 | 0.0001 | 0.0354 | 0.1059 | 0.2239 | 1.0001 |
| CNEI | 300 | 0.3072 | 0.1758 | 0.0958 | 0.1675 | 0.2518 | 0.3900 | 0.8332 |
| NEIF | 300 | 0.0915 | 0.1513 | 0.0101 | 0.0488 | 0.0644 | 0.0838 | 0.8969 |
| IA | 300 | 0.0258 | 0.0391 | 0.0004 | 0.0073 | 0.0153 | 0.0308 | 0.2171 |
| OU | 300 | 0.2524 | 0.2433 | 0.0076 | 0.0963 | 0.1436 | 0.3209 | 1.1338 |
| ER | 300 | 0.0028 | 0.0034 | 0.0001 | 0.0010 | 0.0019 | 0.0034 | 0.0310 |
| GI | 300 | 0.2504 | 0.1015 | 0.1066 | 0.1841 | 0.2259 | 0.2916 | 0.6430 |

2.2.2. *Explanatory variable.* Following Wang [24], the explanatory variables were divided into three components. The entropy method was employed to measure the development levels of three types of new energy industries across 30 provinces from 2013 to 2023. The indicator system is presented in Table 6.

2.2.3. *Control variables.* This study incorporates Industrial Agglomeration (IA), Level of Opening-up (OU), Environmental Regulation (ER), and Government Intervention (GI) as control variables to enhance model robustness. Specifically: IA is defined as the ratio of employed persons (in ten thousand) to administrative area (in square kilometers); OU is the ratio of goods import and export value to regional GDP; ER is measured by the ratio of completed investment in industrial pollution control to industrial value added; GI is the ratio of fiscal expenditure to regional GDP.

2.3. **Data sources.** This study selects panel data from 30 Chinese provinces spanning 2013–2023 as the research sample. The data are primarily sourced from the *China Statistical Yearbook*, the *China Statistical Yearbook on Science and Technology*, the *China Environmental Statistical Yearbook*, the *China Industrial Statistical Yearbook* (2013–2023 editions), official government websites, provincial statistical yearbooks, the WIND database, the CN-RDS database, and the EPS database. Individual missing data points are supplemented using interpolation methods.

Descriptive statistics for each variable are shown in Table 7.

## 3. EMPIRICAL ANALYSIS

3.1. **Baseline regression analysis.** Table 8 reports the benchmark regression results. This study employs a two-way fixed effects model, simultaneously controlling for individual fixed effects and time fixed effects to eliminate the interference of unobservable individual heterogeneity and time trends. Columns (1) to (3) sequentially add core explanatory variables to examine the stability of the regression results.

Column (1) includes only NEII and control variables. The regression coefficient for NEII is 0.3116, passing the 10% significance level test, preliminarily indicating a positive impact of NEII on GTFP. Column (2) adds CNEI to the model. The NEII coefficient increases to 0.4585 and is significant at the 1% level, while CNEI has a coefficient of 0.5050, also significant at the 1% level. This indicates that controlling for CNEI makes the positive effect of

TABLE 8. Baseline Regression Results

| *Variable* | *(1) GTFP* | *(2) GTFP* | *(3) GTFP* |
|---|---|---|---|
| NEII | 0.3116* | 0.4585*** | 0.4530*** |
| | (0.1597) | (0.1630) | (0.1640) |
| CNEI | | 0.5050*** | 0.5088*** |
| | | (0.1534) | (0.1540) |
| NEIF | | | −0.2995 |
| | | | (0.8055) |
| Controls | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes |
| N | 300 | 300 | 300 |

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses

NEII on GTFP more robust, and CNEI also significantly promotes GTFP. (3) Adding NEIF to the equation yields a NEII coefficient of 0.4530 ($p < 0.01$) and a CNEI coefficient of 0.5088 ($p < 0.01$), both highly significant. The magnitude and direction of these coefficients align with those in column (2), confirming that the core findings remain unaffected by the inclusion of NEIF. The NEIF coefficient ($-0.2995$) failed to pass the significance test, indicating that the impact of NEIF on GTFP remains statistically ambiguous. This demonstrates that both New Energy Industry Innovation and Coordination of New Energy Industry promote GTFP.

3.2. **Endogeneity test.** To address potential endogeneity issues such as reverse causality or omitted variables between the core explanatory variables and the dependent variable, this study employs the two-stage least squares (2SLS) method for endogeneity treatment. The lagged value of the core explanatory variable is selected as the instrumental variable. The rationale for this choice is twofold: first, the current explanatory variable exhibits strong temporal correlation with its lagged value, satisfying the correlation condition for instrumental variables; second, the lagged variable is unlikely to be affected by the reverse influence of the current dependent variable, thus meeting the exogeneity condition.

Table 9 reports the 2SLS estimation results. The first-stage regression shows that the coefficient of NEII($t$-1) on NEII is 0.7177 ($p < 0.01$), CNEI($t$-1) has a coefficient of 0.8184 ($p < 0.01$) on CNEI, and NEIF($t$-1) has a coefficient of 0.5651 ($p < 0.01$) on NEIF. Each instrumental variable exhibits a significant positive relationship with its corresponding endogenous variable. Furthermore, the F-statistics for the three first-stage equations were 108.20, 191.31, and 36.02, respectively, all substantially exceeding the empirical critical value of 10. This indicates no weak instrumental variable problem exists, confirming the validity of the instrumental variable selection.

The second-stage regression results show that the coefficient for NEII is 0.4789, significantly positive at the 5% level; the coefficient for CNEI is 0.7667, significantly positive at the 1% level. The coefficient for NEIF is $-2.3368$ but remains insignificant. Overall, these results are consistent with the benchmark regression findings.

3.3. **Robustness test.** To further validate the reliability of the research conclusions, this study conducted robustness tests from the following two dimensions, with results presented in Table 10.

(1) **Truncation treatment.** To eliminate the interference of extreme values on estimation results, all continuous variables were subjected to truncation (Winsorization) at the 1% and 99% quantiles before re-regression. The results show that the NEII coefficient remains significantly positive at 0.4247 ($p < 0.01$), while the CNEI coefficient is 0.4614 ($p < 0.01$). Both coefficients are close in magnitude to those from the baseline regression, indicating that extreme values do not substantially alter the core conclusions.

(2) **Excluding samples from exceptional years.** Considering the potential abnormal impact of the exogenous shock from the COVID-19 pandemic in 2020 on economic variables, this study re-estimated the model after excluding the 2020 samples. The regression results show that the coefficient for NEII is 0.4497 ($p < 0.05$), and the coefficient for CNEI is 0.5178 ($p < 0.01$). The direction and significance of the core variables remain

Table 9. 2SLS Estimation Results

| | First Stage | | | Second Stage |
|---|---|---|---|---|
| *Variable* | *NEII* | *CNEI* | *NEIF* | *2SLS* |
| NEII($t$-1) | 0.7177*** | | | |
| | (0.0418) | | | |
| CNEI($t$-1) | | 0.8184*** | | |
| | | (0.0363) | | |
| NEIF($t$-1) | | | 0.5651*** | |
| | | | (0.0552) | |
| NEII | | | | 0.4789** |
| | | | | (0.2421) |
| CNEI | | | | 0.7667*** |
| | | | | (0.2244) |
| NEIF | | | | −2.3368 |
| | | | | (1.5016) |
| F-statistic | 108.20 | 191.31 | 36.02 | |
| Controls | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| N | 270 | 270 | 270 | 270 |

Note: Instrumental variables are the one-period lagged values of NEII, CNEI, and NEIF. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses

Table 10. Robustness Test Results

| *Variable* | *(1) Winsorization GTFP* | *(2) Excluding 2020 GTFP* |
|---|---|---|
| NEII | 0.4247*** | 0.4497** |
| | (0.1517) | (0.1824) |
| CNEI | 0.4614*** | 0.5178*** |
| | (0.1442) | (0.1629) |
| NEIF | −0.3655 | −0.2978 |
| | (0.7625) | (0.8964) |
| Controls | Yes | Yes |
| Individual FE | Yes | Yes |
| Time FE | Yes | Yes |
| N | 300 | 270 |

Note: (1) All variables are winsorized at the 1% level; (2) The year 2020 is excluded from the sample. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses

fundamentally unchanged, indicating that the research conclusions are not distorted by the pandemic-affected year.

## 4. Conclusion

Against the backdrop of China's "carbon peak and carbon neutrality" strategic goals, this study uses panel data from 30 Chinese provinces spanning 2013–2023 to examine the impact of new energy industry development on industrial Green Total Factor Productivity (GTFP). This paper proposes the CSVF-Malmquist model, which is grounded in structural risk minimization and features better generalization ability and more accurate frontier estimation than traditional DEA-based methods. Combined with the entropy weight method and a two-way fixed effects regression framework, the study yields three key findings.

First, New Energy Industry Innovation (NEII) significantly promotes industrial GTFP, with a baseline coefficient of 0.4530 ($p < 0.01$) and a 2SLS coefficient of 0.4789 ($p < 0.05$). This confirms that R&D investment and human capital accumulation in the new energy sector effectively drive green productivity growth. Second, Coordination of New Energy Industry (CNEI) exerts an even stronger positive effect, with a baseline coefficient of 0.5088 ($p < 0.01$) and a 2SLS coefficient of 0.7667 ($p < 0.01$), indicating that optimizing the coordination between new energy supply and energy demand is a crucial pathway for enhancing industrial green efficiency. Third, the New Energy Industry Foundation (NEIF) does not show a statistically significant impact, possibly because infrastructure development operates as a long-term enabling factor whose effects on green productivity are indirect and subject to time lags. These results are robust to endogeneity treatment using lagged instrumental variables, Winsorization at the 1% level, and exclusion of the COVID-19-affected year 2020.

Based on these findings, the study offers the following policy implications: governments should increase R&D investment in new energy technologies and cultivate innovative talent to strengthen innovation capacity; efforts should be made to optimize the energy supply structure by accelerating the substitution of fossil energy with new energy sources and improving the coordination between new energy power generation and electricity demand; and while infrastructure investment remains essential, policymakers should adopt a patient, sustained investment strategy given its long-term nature.

This study has certain limitations. The insignificance of the NEIF indicator warrants further investigation using more granular data or alternative measurement approaches. Future research could explore the heterogeneous effects across regions or industry sub-sectors, examine potential nonlinear relationships or threshold effects, and incorporate spatial spillover effects among provinces.

## Statements and Declarations

The authors declare that they have no conflict of interest, and the manuscript has no associated data.

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## References

[1] W. Briec and K. Kerstens. The Hicks-Moorsteen productivity index satisfies the determinateness axiom. *Manchester School*, 79(4):765-775, 2011.

[2] L. Brzezicki. Origin and evolution of Malmquist productivity index: Review of the literature. *Central European Economic Journal*, 12(59):102-119, 2025.

[3] R. G. Chambers, R. Färe, and S. Grosskopf. Productivity growth in APEC countries. *Pacific Economic Review*, 1(3):181-190, 1996.

[4] A. Charnes, W. W. Cooper, and E. Rhodes. Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6):429-444, 1978.

[5] J. Chen, M. Du, and C. Huang. Efficiency and its influencing factors of urban water sector in China and major OECD countries. *Journal of Cleaner Production*, 373:Article ID 133885, 2022.

[6] S. Y. Chen. Energy consumption, carbon dioxide emissions and sustainable development of China's industry. *Economic Research Journal*, 44(04):41-55, 2009.

[7] K. M. Cheng and S. E. Li. Total factor productivity index: Evolution, comparison and prospects. *Journal of Statistics*, 3(1):11-26, 2022.

[8] Y. H. Chung, R. Färe, and S. Grosskopf. Productivity and undesirable outputs: A directional distance function approach. *Journal of Environmental Management*, 51(3):229-240, 1997.

[9] D. Dan and Y. Dong. Analysis of the spatiotemporal evolution characteristics of green total factor productivity measurement of China's sports industry. *Preprints*, 2024.

[10] R. Färe, S. Grosskopf, and S. K. Li. Linear programming models for firm and industry performance. *Scandinavian Journal of Economics*, 94(4):599-608, 1992.

[11] E. Jebali and H. Essid. Total factor environmental productivity in the mediterranean countries: A Malmquist–Luenberger index approach. *International Journal of Applied Management and Technology*, 19(1):62-76, 2020.

[12] I. Lacka and L. Brzezicki. The efficiency and productivity evaluation of national innovation systems in Europe. *European Research Studies Journal*, 24(4):471-496, 2021.

[13] F. Z. Li and X. R. Zhang. Green and low-carbon development effects of China's new energy demonstration cities. *Resources Science*, 45(08):1590-1603, 2023.

[14] L. Liang-jun. Eco-efficiency and effectiveness evaluation toward sustainable urban development in China: A super-efficiency SBM-DEA with undesirable outputs. *Environment, Development and Sustainability*, 23(10):14982-14997, 2021.

[15] N. Liang and Q. Zhang. Modified radial Malmquist–Luenberger index models for infeasibility: An application in productivity evaluation of Chinese banks. *Mathematical Problems in Engineering*, 2022:Article ID 9076326, 2022.

[16] X. Y. Liang, X. Lei, and Y. Y. Xie. Measurement and analysis of green total factor productivity in the logistics industry based on the Global Malmquist-Luenberger (GML) index model: A case study of 13 cities in Beijing-Tianjin-Hebei from 2010 to 2020. *Logistics Sci-Tech*, 47(09):5-9, 2024.

[17] X. Liu and J. Huang. China's high-tech industry efficiency measurement with virtual frontier data envelopment analysis and Malmquist productivity index. *Expert Systems*, 39(2):Article ID e12450, 2022.

[18] P. Mitropoulos. Production and quality performance of healthcare services in EU countries during the economic crisis. *Operational Research*, 21(2):857-873, 2021.

[19] J. T. Pastor and C. A. K. Lovell. A Global Malmquist productivity index. *Economics Letters*, 88(2):266-271, 2005.

[20] V. Shestalova. Sequential Malmquist indices of productivity growth: An application to OECD industrial activities. *Journal of Productivity Analysis*, 19(2/3):211-226, 2003.

[21] E. Thanassoulis, R. K. Shiraz, and N. Maniadakis. A cost Malmquist productivity index capturing group performance. *European Journal of Operational Research*, 241(3):796-805, 2015.

[22] D. Valero-Carreras, J. Aparicio, and N. M. Guerrero. Support vector frontiers: A new approach for estimating production functions through support vector machines. *Omega*, 104:Article ID 102490, 2021.

[23] B. Wang and G. T. Liu. Energy conservation, emission reduction and China's green economic growth: Based on the perspective of total factor productivity. *China Industrial Economics*, 05:57-69, 2015.

[24] M. Y. Wang, D. E. Chen, and C. W. Pang. Measurement of high-quality development level and spatiotemporal evolution characteristics of China's new energy industry. *Statistics and Decision*, 41(05):133-136, 2025.

[25] Q. Wang. High-quality development of China's new energy industry: Progress, challenges and countermeasures. *Contemporary Economic Management*, 46(08):64-72, 2024.

[26] S. J. Wang, S. Gao, Y. Y. Huang, et al. Spatiotemporal evolution pattern and prediction of urban carbon emission performance in China based on the super-efficiency SBM model. *Acta Geographica Sinica*, 75(06):1316-1330, 2020.

[27] X. Wang, Y. Wang, and Y. Lan. Measuring the bias of technical change of industrial energy and environment productivity in China: A global DEA-Malmquist productivity approach. *Environmental Science and Pollution Research*, 28(31):41896-41911, 2021.

[28] H. R. Wu and Q. Z. Wu. Efficiency evaluation of local fiscal public cultural service expenditure: Based on a three-stage DEA window model. *Mathematics in Practice and Theory*, 47(3):74-83, 2017.

[29] D. Xie and L. Y. Wang. Energy transition policy and urban green total factor productivity improvement: A quasi-natural experiment based on the new energy demonstration city pilot policy. *Industrial Technology and Economy*, 44(08):107-117, 2025.

[30] J. Yang and A. Meseretchanie. The intermediate role of farmland transfer in the impact of digital financial inclusion on agricultural total factor productivity in China. *Frontiers in Sustainable Food Systems*, 8:Article ID 1345549, 2024.

[31] H. Yang and W. Huang. Spatial dynamics change of mining eco-efficiency in Chinese provinces: A novel assessment framework integrating SBM-DEA and Malmquist-Luenberger models. *Polish Journal of Environmental Studies*, 34(2):1823-1839, 2025.

[32] S. Y. Yang. Theoretical and empirical research on total factor productivity (Master's thesis). *Tianjin University*, 2006.

[33] X. F. Yin and W. B. Duan. Sources of China's total factor productivity: Theoretical construction and empirical evidence. *Nankai Economic Studies*, (1):95-116, 2016.

[34] H. L. Zhang. Research on the development of new energy in China (Doctoral dissertation). *Jilin University*, 2014.

[35] S. Zhong and H. Wang. The effect of total factor productivity of forestry industry on CO2 emissions: A spatial econometric analysis of China. *Scientific Reports*, 11(1):Article ID 14200, 2021.

[36] Q. Zhu, C. Liu, X. Li, et al. The total factor carbon emission productivity in China's industrial sectors: An analysis based on the global Malmquist-Luenberger index. *Sustainable Energy Technologies and Assessments*, 56:Article ID 103094, 2023.