Evaluating China's high-quality economic development model: the example of the Yangtze River region

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China's contemporary leadership aspires to advance the transition from a productivity-first economic model to a technology- and ecology-first high-quality system (Xinhua 2024). This study analyses this transition from a regional perspective, using the example of the Yangtze River region. Due to its significance, diversity and ongoing development initiatives, this region is appropriate for in-depth economic analysis. We apply a composite principal component analysis–slacks-based measure model (PCA–SBM) to evaluate regional economic development holistically and identify the root causes of economic inefficiency (Deng et al. 2020). This approach enables us to calculate the productivity of 12 provinces in the Yangtze River region from 2012 to 2021. This study's most significant methodological and innovative contributions include combining an input–output model with the PCA–SBM model to evaluate regions' transition to a high-quality economic model. The significant results are twofold. (1) The eastern regions represent the efficient deployment of human and welfare resources; however, pollution hinders the road to high-quality development. (2) The western regions have higher forest coverage rates and superior air quality; however, more than labor efficiency is required to accelerate urbanization. No direct correlation is evident between economic development and high-quality efficiency. This is a *novel discovery* that challenges previous research findings. Among the study's limitations are the small number of indicators used and the need for additional data, which can be addressed in future research.

Keywords:
high-quality economy,
economic transformation,
PCA–SBM model,
the Yangtze River region,
14th Five-Year Plan of China

Introduction

China is confronting multiple short- and long-term challenges such as tensions in the real estate market and the financial system and an ageing population, declining birth rates, severe environmental problems, fierce global technology competition and decelerating GDP growth, among others. From a broader perspective, the primary reasons behind these challenges include the exhaustion of the former driving factors of GDP growth that included a cheap unskilled or semiskilled labor force, cheap fuels and raw materials and considerable investment in traditional heavy industries. This indicates a transition from an *extensive economic development model*, based on quantitative factors of GDP growth such as the mere quantity of labor and capital, to an *intensive development model* that relies on qualitative factors such as research, development and innovation (R+D+I); highly skilled human capital (knowledge-based economy), and economic structure upgrading with reduced regional disparity and income inequality (Losoncz 2017). The transition requirements can be examined using the United Nations human development index (HDI), which measures a country's or region's human development comprehensively based on per capita income, life expectancy and education; however, the HDI does not include the efficiency of the input–output process and resource waste.

To respond to the current challenges and promote long-term, sustainable economic development, the primary task is to transform China into a *high-quality economy*[1] that is characterized by five factors (Pacetti 2016) of *sustainability*, *innovation*, *efficiency*, *stability* and *coordination.* A high-quality economy should employ innovative methods to boost economic efficiency and productivity while avoiding irreparable harm to environmental and natural resources, securing regional coherence and establishing regional connections (Li–Yi 2020).

Formerly, scholars have only weighted indicators to fit the total score and neglected the inclusion of input–output (supply–demand) considerations to determine whether *social resources are used efficiently and environmental issues are solved appropriately* (Ding et al. 2016, Tan–Lu 2015). This study fills this *research gap* by arguing and demonstrating that the essence of a high-quality economy is to maximize the

[1] The concept of high-quality development was first introduced at the Communist Party of China's (CPC) 19th National Congress in 2017. President Xi Jinping repeatedly emphasised the importance of high-quality development, stressing its significance in 2021. High-quality development refers to shifting the economic growth model from crude to intensive, with a strong focus on innovation. Rather than relying solely on traditional factors such as labor, capital and land, growth will be driven by new, innovative elements such as information technology, big data and artificial intelligence. High-quality development is intended to improve efficiency, equity, sustainability and security. Obsolete production capacities and technologies will be phased out in stages, while emerging green industries and renewable resource technologies are developed. This approach is expected to pave the way for the emergence of an innovative, green development model that promotes a harmonious relationship between humans and nature (Xinhua 2024).

efficient use of input resources, using a composite principal component analysis (PCA)–slacks-based measure (SBM) (PCA–SBM) model[2] to achieve this goal.

Referencing the indices outlined in *China's 14th Five-Year Plan Guidance*, this study constructs a novel evaluation framework for economic development by establishing an *index system* based on an efficiency model. This regional case study explores the differences in the economic development of the Yangtze River region's eastern and western areas in the transition to a high-quality economy. Several factors justify its selection for our investigation. First, it includes some of China's most economically active provinces, encompassing Shanghai, Wuhan and Chongqing. Second, it is the core of China's regional economic development, and its coastal area traverses China from the west to the east, comprising 40% of the nation's population and GDP on 20% of China's territory. China's GDP and industrial output are greatly influenced by economic trends in this region, offering a mesocosm for investigating a wide range of policy-related, social, environmental and economic issues. Third, given the region's economic significance, diversity and ongoing development initiatives, it is an appropriate object for in-depth economic and development policy analyses.

This study complements the broader body of research covering China's transition to a high-quality economic model. Losoncz (2017, 2023) analyzed the dilemmas of China's shift to a new growth trajectory considering the antecedents by mapping China's global environment and highlighting the effect of globalization on China and China's impact on globalization. Chen proposed the detailed methodological tools applied in this study using real-world data to confirm the model's validity. In addition, in-depth analyses have been conducted in several key industries (Chen 2023). The author noted that the tourism industry's future lies in technological innovation (Chen 2022). Analyzing the relationship between the electricity sector and high-tech industries using an east–west regional approach, Chen (2024) concluded that electricity consumption significantly affects software businesses' revenue, while hydropower and thermal power generation have significant adverse effects.

The remainder of this paper is organized as follows. The literature review highlights current mainstream trends. Then, the data collection, research design, methodology and assumptions are described. After that, the results based on the models are presented, followed by the discussion of the results; and finally, summary and conclusions are provided.

[2] Principal component analysis (PCA) and the slacks-based measure (SBM) are combined into the PCA–SBM model, presenting an integrated approach. PCA reduces the number of variables while retaining all relevant information for dimensionality reduction. Data envelopment analysis (DEA) assesses the comparative efficiency of decision-making units (DMUs) to determine the top performers within a group. SBM, which is a DEA variant, includes input and output slacks to account for inefficiencies and identify areas for improvement (Deng et al. 2020).

Literature review

Along with the introduction of the new concept for China's high-quality economic transformation in the 2020s, increased attention has been paid to the digital economy, social welfare, carbon neutrality and regional coordination. High-quality development is a new target for economic transformation covering these aspects (Fang 2022). The prerequisite for achieving economic transformation is industrial structure upgrading by promoting a shift from low-value-added to high-value-added fields (Cheong–Wu 2014).

The two regional economic development econometric models are comprehensive evaluation and input–output analysis. Comprehensive evaluation of economic development involves assessing a wide range of factors that contribute to a region's economic growth, prosperity and overall well-being. This approach typically considers multiple dimensions of economic development using PCA, weighted scoring, hierarchical analysis and other approaches. PCA was introduced by Karl Pearson in 1901 and further developed by Harold Hotelling in the 1930s and is a key method for dimensionality reduction. Furthermore, PCA scores, which indicate the data's projection onto these components, are an effective tool for evaluating and summarizing complex datasets (Pearson 1901, Hotelling 1933). Jia Wanjing (2007) collected 12 economic indicators from Jiangsu Province using PCA to extract common factors and calculate the composite score based on typical factors. The primary factors affecting the composite score included local taxation, industrial profits and central government taxes. Ma et al. (2019) established a weighted scoring method, proposing a high-quality development index covering high-quality supply and demand, economic operation and openness to the outside world for 30 provinces. The authors concluded that China's high-quality economic development is regionally unequal and differences decrease from the east to the west. Cui et al. (2022) examined government guidance funds for the Beijing–Tianjin–Hebei region between 2005 and 2018 and examined 518 policies, using three dimensions of policy intensity, objectives and measures to construct a policy efficiency evaluation system. The study conducted a hierarchical analysis to determine whether government funds and performance are influential, concluding that the efficiency of policy-related fund allocation by the government required improvement. Yin Xiangfei (2019) proposed a network–input–output–service provider index[3] to empirically analyze China's local data, decompose it from the production and environmental governance stage and compare sustainability under different economic growth models.

Many studies above calculated composite scores by assigning weights to their indicators after index quantification. However, evaluating high-quality economies did

[3] The Network–IO–SP analyses evaluate aspects related to the network (network), input–output (IO) and a service providers (SP). It can be applied to conduct network analysis, performance measurement or assess the role of service providers in the context of network services.

not involve each region's supply and demand perspectives of economic efficiency. The input–output analysis is another method to evaluate a regional economy's performance. It is a widely used tool for evaluating the economic impact of regional development initiatives. It initially studies the interdependence of a region's industries and calculates the impact of changes in one sector on the whole regional economy. It begins with the assumption that economic progress is due to more efficient utilization of inputs such as labor, capital and raw resources. Leontief first devised the input–output model in the 1930s, and its impact has been significant and wide-ranging, from regional and sectoral studies to environmental impact assessment. This model depicts the flow of products and services between different sectors of an economy, providing insights into how outputs from one sector are used as inputs in another (Leontief 1987). Data envelopment analysis (DEA), another input–output analysis introduced by Charnes et al. (1978), is an empirical tool for measuring the productivity efficiency of decision-making units. It is particularly useful in assessing the socioeconomic impact of policies by comparing inputs and outputs, given the subjective nature of policy evaluation. Its primary characteristics include measuring relative efficiency by managing numerous inputs/outputs without specified weights, building an efficiency frontier, being non-parametric, incorporating slack variables and enabling broad applicability with both static and dynamic analysis (Charnes et al. 1978, 1994, 1997). Building on this, Tone developed the SBM model as a non-radial efficiency measure, enhancing the traditional DEA approach by addressing input–output slackness and accounting for undesirable outputs such as environmental pollution. This makes the SBM model a more accurate and realistic method for evaluating economic efficiency, particularly in the context of regional economic development where policy impacts are multifaceted (Tone 2001, 2015). In most articles that have used DEA models for efficiency calculations, input–output analysis has been considered from the perspective of one industry or in terms of a specific environmental issue. For example, Yan et al. (2018) evaluated the environmental sustainability of 48 cities, assessing energy–economic–environmental efficiency (3Es) based on improved technologies, ranking the eastern region highest in 3E performance, followed by the central region, with the western region as the lowest (Yan et al. 2018). Quan Liang–Zhao (2019) assessed green inefficiency values and industrial enterprises' green total factor productivity in 30 Chinese provinces from 2007 to 2016, analyzing their influence using the system generalized method of moments model.

In contrast to previous studies, this study combines the above categories and applies the PCA–SBM model for comprehensive evaluation. Many previous studies have used the PCA–DEA model, demonstrating the effectiveness and rationality of combining these two methods. For example, PCA is integrated with DEA to address the issue of dimensionality in DEA models. The combination of DEA and PCA improves the complexity and big dimensionality of the data used in airline network analysis. Deng et al. (2020) used PCA to simplify indicator dimensions and SBM–DEA to evaluate performance with and without carbon emissions constraints, revealing significant regional differences and determining that low scale efficiency hampers logistics development. The PCA–DEA method to construct a performance evaluation system for talent housing strategies in nine Nanjing districts is applied. The study assessed the effectiveness and efficiency of talent housing programs' input–output using BCC and CCR models.

When conducting efficiency analysis, efficiency is divided into high-quality (technical) efficiency, pure technical efficiency and scale efficiency, categorizing and examining effectiveness from these three perspectives (Table 1).

Table 1

Definition of efficiency

Efficiency	Explanations
High-quality efficiency (technical efficiency, TE)	High quality integrated economic efficiency is a comprehensive evaluation of various aspects such as the efficiency of resource allocation and the use of each decision unit. TE=PTE*SE
Pure technology efficiency (PTE)	Based on factors such as management and technology, pure technical efficiency refers to the production efficiency of the decision-making unit. Pure technical efficiency indicates the ability to attain maximum economic output and minimum negative environmental output.
Scale efficiency (SE)	Scale efficiency refers to the economic efficiency of scale formed by province through economic development planning and cooperation with other provinces in other Yangtze River basins.

Source: authors' construction based on Long et al. (2016).

This study innovatively considers total factors including five indicators to evaluate economic performance referencing the 14th Five-Year Plan indicators system,[4] applying input–output analysis to measure economic efficiency in 12 regions along the Yangtze River Delta based on the definition of a high-quality economy. The DEA model's characteristics noted above enable a more rigorous analysis of regional economic vulnerability and development policy coordination than other methods.

[4] The Outline of the 14th Five-Year Plan for Economic and Social Development (2021–2025) and Long-Range Objectives through 2035, developed in accordance with the Central Committee of the Communist Party of China's recommendations, focuses on innovation-driven, low-carbon growth, urban–rural integration and social inclusion. It comprises a comprehensive indicator system that reflects the government's priority areas. This paper builds on the design principles of these indicators and collects relevant data across the specified areas (ADB 2021).

Data collection, research design, methodology and assumptions

This study's *data* are primarily obtained from the China Stock Market & Accounting Research and the National Bureau of Statistics (NBS) databases. Economic efficiency data are retrieved from NBS, and macroregional data from 2012 to 2021 are obtained from provincial statistical yearbooks. The data from publicly available government databases are accurate, representative and objective. The study uses the 14th Five-Year Plan indicators as a measurement tool, and Table A1 (see in Appendix) presents the 15 selected indicators and explanations from 18 indicators. Because the government's 14th Five-Year Plan was formulated from a macroeconomic perspective and kept regional data inaccessible, some data are unavailable; however, these 15 indicators cover the five categories identified in the plan. In addition, this selection already includes additional similar signs. As a result, these 15 indicators are sufficient for assessing the five areas under examination and for effective calculation of economic efficiency. The individual stages of the research are as follows.

PCA–SBM model setting

Step 1: Data dimensionality reduction with PCA

This study organizes the data dimensions based on the correlation or covariance matrix of the original variables to extract the primary data information and reduce concerns of duplicate data features caused by multiple covariances while retaining relevant information (Hotelling 1933). This study applies PCA to the nine input indicators and downscale them to several principal components (PCs). Table 2 presents the resulting indicators.

Table 2

Indicator designs

Indicators	Name	Name in the models
Input		
R&D spending of industrial enterprises above the scale (10,000 yuan)	x1	PC1: In1 PC2: In2 PC3: In3
The number of domestic invention patent applications received (items)	x2	
Overall grain production capacity (hundreds of million tons)	x3	
The number of certified (assistance) doctors (1,000 persons)	x4	
The number of urban and rural residents' social old-age insurance participants (10,000)	x5	
Average number of nursery school students per 100,000 population (persons)	x6	
Revenue from software business (100 million yuan)	x7	
Disposable income growth per capita (%)	x8	
Surveyed urban unemployment (1,000 person)	x9	

(Table continues on the next page.)

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Indicators	Name	Name in the models
Output		
Reginal gross domestic products (CNY 100 million)	y1	Ou1
Workforce productivity (yuan/1 person)	y2	Ou2
Urbanization rate (%)	y3	Ou3
Days of air quality equal to or above grade II (day)	y4	Ou4
Forest coverage rate	y5	Ou5
Undesire output		
Emission of exhaust gas (10,000 tons)	z1	Undesire output1

Step 2: Calculating the current period's standards efficiency using a non-oriented SBM model with undesirable output

Economic efficiency can be calculated from input, output and non-oriented perspectives. Unlike Charnes, Cooper and Rhodes (CCR) (1978) and Banker, Charnes and Cooper (BCC) (1984) approaches that focus on overall efficiency but do not consider input excesses or output shortfalls, the SBM model accommodated such inefficiencies from a non-oriented angle, including undesirable outcomes (Tone 2001, 2015). We use a non-oriented SBM model, which is designed to accommodate undesirable outcomes. Tone (2015) proposed the non-oriented SBM model by modifying the SBM model to explicitly include undesirable outcomes. This means that the efficiency statistic considers how successfully a DMU uses inputs to produce desired outcomes as well as how it manages undesirable outcomes. For example, in environmental applications, the model can account for pollution levels and resource efficiency. Furthermore, a non-oriented SBM can detect and evaluate efficiency by considering improvements in inputs and outputs simultaneously, rather than focusing solely on one direction. As a first step in our investigation, we applied the standard SBM model to establish a general overview of the distribution of efficiency among DMUs. In the standard DEA model, efficiency is determined by comparing inputs and outputs. Efficient DMUs receive a score of $\theta = 1$, indicating full efficiency, while inefficient DMUs receive a score that is less than one. However, in other circumstances, all effective DMUs can receive the same efficiency score of one, which makes it difficult to discern between highly efficient DMUs. This first inquiry is crucial for understanding general efficiency and building a framework for the subsequent application of the super-efficiency SBM, which allows for more detailed discrimination among highly efficient DMUs. This comprehensive approach offers a holistic view of efficiency, making it ideal for complex systems that require multi-dimensional optimization. We apply efficiency comparisons to identify how key policies affect efficiency according to the following formula:

$$\theta^* = \min_{\lambda,s^-,s^+} \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{S_i^-}{x_{i0}}}{1 + \frac{1}{q+h}\left(\sum_{r=1}^{q} \frac{S_r^+}{y_{r0}} + \sum_{k=1}^{h} \frac{S_k^-}{b_{k0}}\right)}$$

$$s.t \begin{cases} x_{i0} = \sum_{j=1}^{n} \lambda_j x_{ij} + S_i^-, i = 1, \dots, m \\ y_{r0}{}^g = \sum_{j=1}^{n} \lambda_j y_{rj} - S_r^+, r = 1, \dots, q \\ b_{k0}{}^b = \sum_{j=1}^{n} \lambda_j b_{kj} + S_k^-, k = 1, \dots, h \end{cases} \quad (1)$$

where:
$\theta^*: the\ efficiency\ value\ of\ DMU(x_0, y_0)$
$S_i^-: input\ excess.$
$S_r^+ : output\ shortfall.$
$S_k^- : undesirable\ output\ excess.$
$[x_{i0}] is\ m\ input\ indicators, where: i = 1, 2, \dots\dots, m.$
$[y_{r0}] is\ q\ output\ indicators, where: r = 1, 2, \dots\dots, q.$
$[b_{k0}]\ is\ h\ undesirable\ output\ indicators, where: k = 1,2, \dots\dots, h.$
$\lambda = [\lambda_1, \lambda_2, \lambda_3 \dots \lambda_n]^T is\ called\ the\ intensity\ vector.$

Source:: Dealing with undesirable outputs in DEA: A slacks-based measure (SBM) approach (Tone 2015).

Step 3: Robustness test to calculate the entire period's super-efficiency using a non-oriented SBM model with undesirable output

In most DEA models, the top-performing decision-making units (DMUs) [5] have an efficiency score of $\theta^* = 1$, suggesting that all variables are considered efficient. However, many DMUs often receive the same efficiency score, which makes it difficult to discern between them. To address this issue, Tone offered various techniques for ranking top performers, which is known as the super-efficiency problem (Tone 2002). Beyond this, unlike current efficiency, which focuses on isolated time periods, the entire period's efficiency (particularly within dynamic DEA) incorporates carry-over activities between periods. This approach provides a comprehensive assessment of sustained performance and is crucial for long-term planning. The dynamic DEA model was the first innovative contribution to this field, and a model using the SBM framework is developed.

[5] In DEA, DMUs are the entities under evaluation or comparison such as firms, organisations or entities that transform inputs into outputs. In this study, DMU refers to the 12 provinces along the Yangtze River region.

Therefore, further measurement is conducted via super-efficiency analysis, which can check the weak efficiency state in the calculation process based on the following formula:

$$\theta^{*} = \min_{\lambda,s^{-},s^{+}} \frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{S_i^{-}}{x_{i0}{}^{t}}}{1-\frac{1}{q+h}\left(\sum_{r=1}^{q}\frac{S_r^{+}}{y_{r0}{}^{t}}+\sum_{k=1}^{h}\frac{S_k^{-}}{b_{k0}{}^{t}}\right)}$$

$$s.t\begin{cases} x_{i0}{}^{t} \geq \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_j{}^{t}x_{ij}{}^{t}+S_i^{-}, i=1,\ldots,m \\ y_{r0}{}^{t} \leq \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_j{}^{t}y_{rj}{}^{t}-S_r^{+}, r=1,\ldots,q \\ b_{k0}{}^{t} \geq \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_j{}^{t}b_{kj}{}^{t}+S_k^{-}, k=1,\ldots,h \end{cases} \tag{2}$$

$When\ \theta *= 1, the\ DMU\ is\ efficient.$

$When\ \theta * < 1, The\ DMU\ is\ inefficient\ and\ there\ is\ a\ need\ to\ improve\ the\ output\ of\ the\ investment.$

Source: A slacks-based measure of super-efficiency in data envelopment analysis (Tone 2002).

We present the methodological design in Figure 1. Our analysis is based on the following three assumptions:

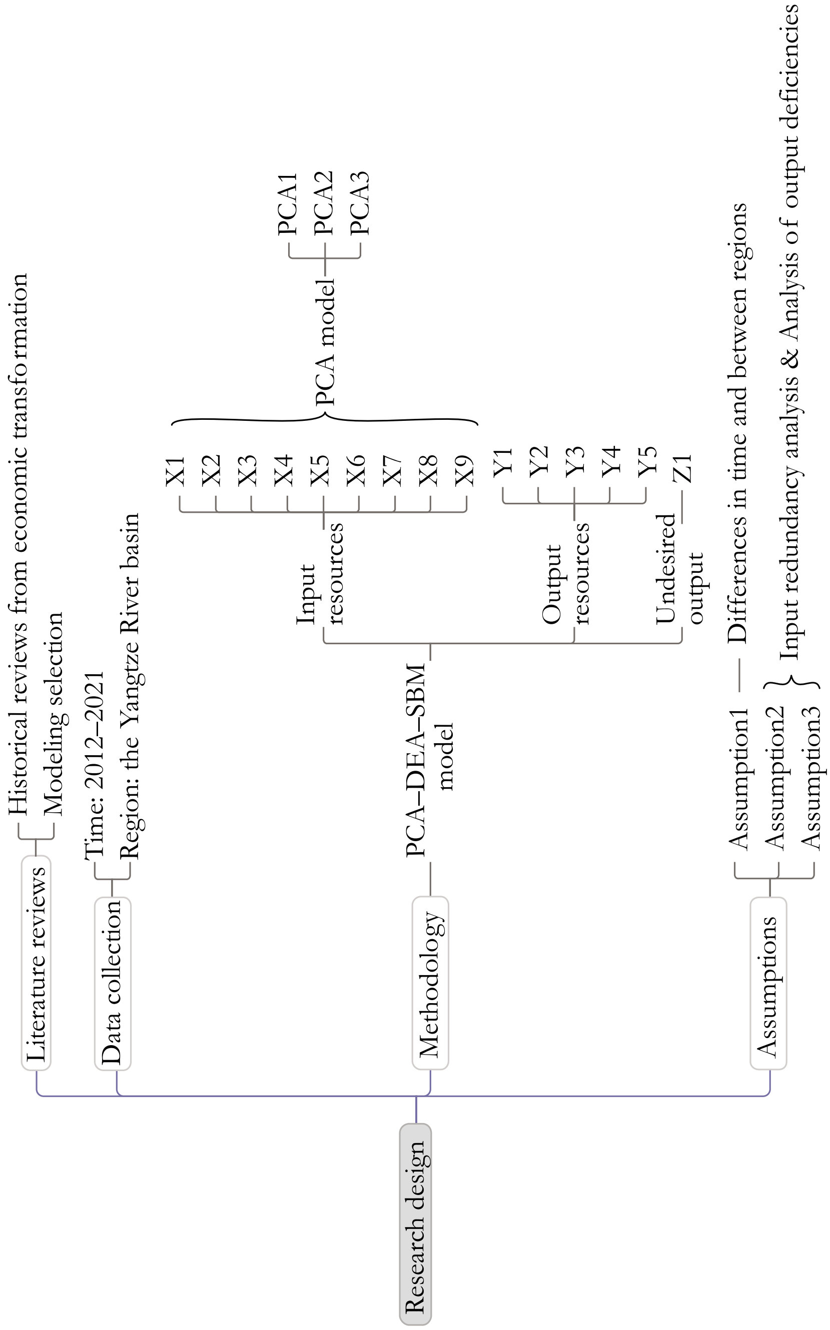
Assumption 1: Each region's development grows annually, and high-quality efficiencies in developed regions are higher than those in less developed regions.

Assumption 2: Eastern regions benefit more extensively from technological, labor and welfare input resources than western regions.

Assumption 3: Western regions have less pollution output resources than the eastern regions.

Figure 1

Research design framework



Source: authors' construction illustrating the study's structure.

Results

PCA–SBM analysis

Dimension reduction: PCA

Based on the Cooper et al. (2007) book, DMUs should be at least max [(m × s; 3 × (m s))], where m is the number of inputs and s is the number of outputs. This study examines data from 12 provinces and 15 macroeconomic indicators from 2012 to 2021. With 12 provinces and data spanning 10 years, the annual data for each province is considered to be a distinct DMU; therefore, the total number of DMUs is 120.

Hence, the input indicators must be reduced. By constructing a correlation matrix, PCA can combine PC scores linearly. The PCA applied in the scope of this study fits nine input indicators into three primary datasets. We use two statistical techniques to evaluate the suitability of data for PCA: *Bartlett's test of sphericity* and the Kaiser–Meyer–Olkin (*KMO*) test (Bartlett 1950), as indicated in Table 3.

Table 3

KMO and Bartlett test results

KMO		0.709
Bartlett test	approx. chi-square	1,249.55
	df	36
	p value	0

Source: authors' calculation using SPSS.

The *KMO* test assesses the correlation between variables, and the result is 0.709, indicating that the nine data indicators can be better analyzed using PCA (Roweis 1997). *Bartlett's test of sphericity* assesses whether the correlation matrix is an identity matrix, implying no correlations between variables. A Bartlett p-value of $0.00 < 0.05$ passes the reliability test, indicating that the data can be analyzed using PCA.

Following the z-score normalization of the original data for the indicators, we combine the components of the indicators into three PCs with respective variance eigenvalues of 50.392%, 23.19% and 12.981% (Table 4) (Kappal 2019). According to Kaiser's criterion, we retain all PCs with eigenvalues > 1 (Kaiser 1960), which makes it possible to summarize most of the information in the data clearly and concisely.

Table 4

Principal component eigenvalues and variance rates of indicators

Total variance explained			
PCA	eigen	% of variance	cum. % of variance
1	4.535	50.392	50.392
2	2.087	23.19	73.582
3	1.168	12.981	86.562
4	–	–	–
5	–	–	–
6	–	–	–
7	–	–	–
8	–	–	–
9	–	–	–

Source: authors' calculation using SPSS.

Table 5

Factor loadings

Items	Loadings			Communalities
	PC 1	PC 2	PC 3	
R&D spending of industrial enterprises above the scale (10,000 yuan)	0.825	–0.472	–0.043	0.906
The number of domestic invention patent applications received (items)	0.827	–0.457	–0.013	0.892
Overall grain production capacity (hundreds of million tons)	0.817	0.515	0.068	0.938
The number of certified (assistance) doctors (1,000 persons)	0.952	0.175	–0.036	0.938
Number of urban and rural residents' social old-age insurance participants (10,000)	0.644	0.733	0.005	0.952
Average number of nursery school students per 100,000 population (persons)	–0.079	0.377	–0.802	0.792
Revenue from software business (100 million yuan)	0.706	–0.665	0.047	0.942
The disposable income growth per capita (%)	–0.286	0.306	0.699	0.663
Surveyed urban unemployment (1,000 person)	0.772	0.381	0.161	0.766

(Table continues on the next page.)

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Linear combination coefficient matrix			
Items	Component		
	PC 1 innovation and technology resources	PC 2 labor resources	PC 3 welfare resources
R&D spending of industrial enterprises above the scale (10,000 yuan)	0.387	–0.327	–0.04
The number of domestic invention patent applications received (items)	0.388	–0.316	–0.012
Overall grain production capacity (hundreds of million tons)	0.384	0.357	0.063
The number of certified (assistance) doctors (1,000 persons)	0.447	0.121	–0.033
Number of urban and rural residents' social old-age insurance participants (10,000)	0.303	0.507	0.005
Average number of nursery school students per 100,000 population (persons)	–0.037	0.261	–0.742
Revenue from software business (100 million yuan)	0.331	–0.46	0.043
The disposable income growth per capita (%)	–0.134	0.211	0.647
Surveyed urban unemployment (1,000 person)	0.362	0.264	0.149

$$\begin{aligned} PCA1 &= 0.387 * x_1 + 0.388 * x_2 + 0.384 * x_3 + 0.447 * x_4 + 0.303 * x_5 - 0.037 * x_6 + 0.331 * x_7 \\ &\quad - 0.134 * x_8 + 0.362 * x_9 \\ PCA2 &= -0.327 * x_1 - 0.316 * x_2 + 0.357 * x_3 + 0.121 * x_4 + 0.507 * x_5 + 0.261 * x_6 - 0.46 * x_7 \\ &\quad + 0.211 * x_8 + 0.264 * x_9 \\ PCA3 &= -0.04 * x_1 - 0.012 * x_2 + 0.063 * x_3 - 0.033 * x_4 + 0.005 * x_5 + -0.742 * x_6 + 0.043 * x_7 \\ &\quad + 0.647 * x_8 + 0.149 * x_9 \end{aligned} \tag{3}$$

Source: authors' calculation using SPSS.

Based on the contribution of these factor loadings (Table 5) and the linear combination coefficient matrix, we obtain the above equation based on the eigenvalues (three formulas in Table 3). We calculate three indicator scores consisting of nine indicators for two provinces from 2012 to 2021 using a PCA formula. To better classify these indicators, *innovation and technology resources* were defined as PC 1, *labor resources* as PC 2 and *welfare resources* as PC 3.

To address the requirement of DEA for non-negative input variables, we normalized the PCA before applying DEA (Pastor–Ruiz 2007, Shanmugam–Johnson 2007). We adopt the min–max normalization linear function to linearize the original data to the [0, 1] range to address the presence of negative PCA scores, which are not suitable for DEA as it requires non-negative inputs and outputs. The min–max normalization method ensures that all transformed PCA scores fall within the [0,1] range to enable their use in the DEA model. We normalized data are used for the calculated result, where X is the original data (Kappal 2019).

$$x^n = \frac{x - min(x)}{max(x) - min(x)}$$

$$x^n: the\ normalized\ data$$

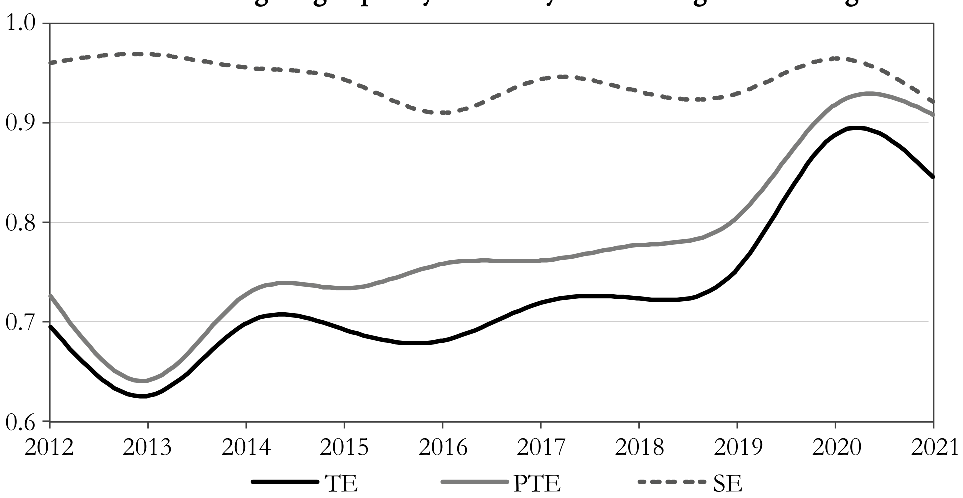
We employed iDea software[6] to apply the SBM model, setting the DMUs to 120, inputs to 3, outputs to 5 and the undesirable output to 1. (Undesired outputs such as environmental pollution are not included in the outputs.) We calculate efficiency using a global frontier, non-oriented, standard efficiency approach.

Spatio-temporal differences

From 2014 to 2019, the quality of economic efficiency across China's provinces exhibited minimal fluctuation, maintaining a steady upwards trend. The efficiency value reached its lowest point in 2013, followed by a peak in 2020, after which it began to decline. High-quality efficiency (technical economic efficiency) displayed an upwards trend from 2011 to 2021. The trend of pure technical economic efficiency was similar, suggesting that government management and resource allocation boosted technical economic efficiency. Scale efficiency remained around 0.9–1 from 2012 to 2021, indicating that the scale and structure of inputs were reasonable and the value-added benefits from scale expansion remained reasonable (Figure 2).

Figure 2

Trend of average high-quality efficiency in the Yangtze River region

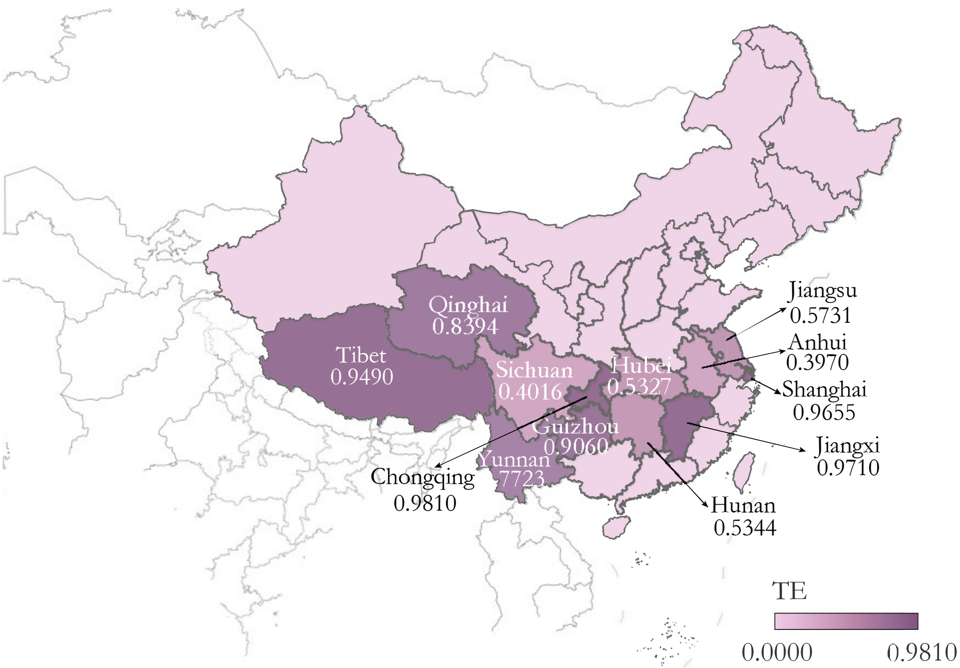


Source: authors' constructions based on model results.

[6] https://github.com/zsffgzs/iDEA

Figure 3

Average high-quality (technical) efficiency distribution in the Yangtze River region



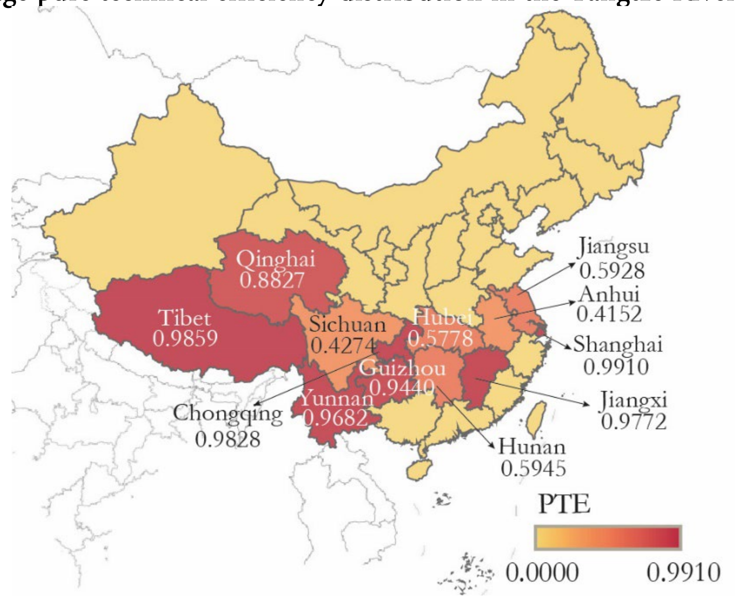
Notes: map bases on longitude (generated) and lattitude (generated). Color shows average TE. The marks are labeled by provinces and average of TE. Details are shown provinces. The data is filtered on average of TE, which ranges from 0 to 1.

Source: authors' construction using Tableau software.

We compose the efficiency values for each province are decomposed based on the accounting results. The average efficiency values between 2012 and 2021 are calculated per province and then plotted using Origin 2021 software. According to the high-quality efficiency analysis, Sichuan Province and Hubei Province, which are the core strengths of the eastern and central regions, do not score the highest for technical efficiency compared with the distribution of GDP production output described in the previous section. Previous literature has generally used GDP and other gross product indicators to evaluate economic development (Rahman et al. 2017); however, the deficiency of this method is that environmental pollution caused by rapid economic development has become the most critical deduction. Therefore, Sichuan, which is the central province for local development in western China, and Hubei, which is the centre of China's hinterland, must strengthen environmental pollution management. Notably, Chongqing is strong and effective in terms of high-quality economic efficiency, indicating that it has performed well in terms of GDP and environmental protection, with corresponding management from the government (Figure 3). The differences in pure technical efficiency between the eastern and western regions are similar to the case of high-quality economic efficiency. Provinces with heavy industry and large mineral reserves such as Sichuan, Hubei and Jiangsu emit considerable pollution, making these provinces less pure in technical efficiency (Figure 4). Regional differences in scale efficiency, which primarily measures the impact of resource inputs on policy efficiency, are less pronounced than the other two efficiencies. Qing Hai, Tibet, Chongqing, Hunan, Jiangxi, Jiangsu and Shanghai had scale efficiencies of 1 in 2021. The scale efficiency of these provinces remained unchanged (i.e. the scale and structure of inputs were reasonable). The scale efficiency for the remaining provinces was decreasing, indicating that policy output increases were smaller than input increases, indicating that policy implementation must improve (Figure 5).

Figure 4

Average pure technical efficiency distribution in the Yangtze River region

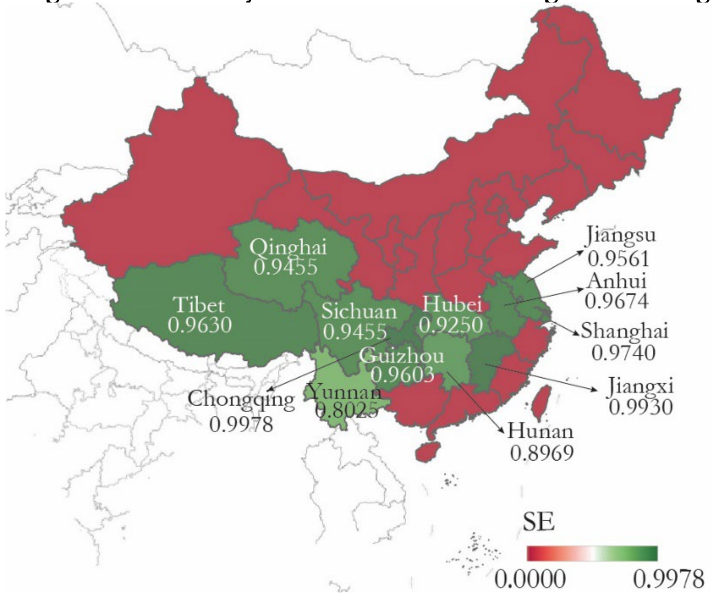


Notes: map bases on longitude (generated) and lattitude (generated). Color shows average PTE. The marks are labeled by provinces and average of PTE. Details are shown provinces. The data is filtered on average of TE, which ranges from 0 to 1.

Source: authors' construction using Tableau software.

Figure 5

Average scale efficiency distribution in the Yangtze River region



Notes: map bases on longitude (generated) and lattitude (generated). Color shows average SE. The marks are labeled by provinces and average of SE. Details are shown provinces. The data is filtered on average of TE, which ranges from 0 to 1.

Source: authors' construction using Tableau software.

Input redundancy analysis

Redundancy analysis can be defined as the difference between the ideal and the actual values of inputs to achieve optimal efficiency (Ul Hassan Shah et al. 2024). We conduct an input redundancy analysis using the data from 2012 to 2021 to better understand the potential for improving ecological inputs, particularly for provinces that were identified as relatively inefficient in the DEA. The slack[7] value refers to the amount of excess output or shortfall in input that will not affect the optimal solution, and the normal calculation method is divided by the original data value to calculate input redundancy and determine relative rate (Tone 2002). Input redundancy rates are calculated by dividing input item slack by input quantity, and output deficiency rates are calculated by dividing output item slack by output quantity (Podinovski 2004). Within the PCA, Slack_ln1; 2; 3 (the abbreviation for PC1, PC2 and PC3 inputs) represents science and technology, human and welfare resources, respectively.

[7] In various analytical contexts, slack refers to how an activity or a resource can be delayed or underutilised without negatively affecting the overall process or outcome (Tone 2002, 2015).

Table 6

Input slack value and redundancy rate in 2021 by region

District	Provinces	Slack_In1	Redundancy rate, %	Slack_In2	Redundancy rate, %	Slack_In3	Redundancy rate, %
Western region	Qinghai	0.00	0.00	0.00	0.00	0.00	0.00
	Tibet	0.00	0.00	0.00	0.00	0.00	0.00
	Sichuan	0.14	21.19	0.51	55.67	0.11	18.64
	Yunnan	0.00	0.00	0.02	2.69	0.13	35.61
	Chongqing	0.00	0.00	0.00	0.00	0.00	0.00
	Guizhou	0.01	2.78	0.15	17.37	0.06	29.76
Average		0.02	3.99	0.11	12.62	0.05	14
Central region	Hubei	0.03	5.28	0.36	44.44	0.15	25.63
	Hunan	0.00	0.00	0.00	0.00	0.00	0.00
	Jiangxi	0.00	0.00	0.00	0.00	0.00	0.00
Average		0.01	1.76	0.12	14.81	0.051	8.54
Eastern region	Anhui	0.1	19.47	0.59	65.53	0.04	8.87
	Jiangsu	0.00	0.00	0.00	0.00	0.00	0.00
	Shanghai	0.00	0.00	0.00	0.00	0.00	0.00
Average		0.03	0.06	0.2	0.22	0.01	0.03

Source: authors' calculations based on model results.

According to the allocation of Slack_ln1 (science and technology resources) for the provinces, Sichuan Province can improve its use of science and technology resources the most, reaching 21.19% (Table 6). In practical terms, this means that achieving a 21.19% improvement in the PC1 requires strategically targeted adjustments to these underlying indicators from the equation (3). Therefore, the local Sichuan government should focus its reform on enhancing research and development investments, increasing the number of patents and improving doctors' certifications, as these areas significantly impact the PCs. This is followed by Anhui Province, where the utilisation rate still needs to be improved by 19.47%. Based on the distribution of Slack_ln2 (labor resources) for the provinces, Hubei (0.36), Sichuan (0.51) and Anhui (0.59) Provinces need to increase efficiency when using labor resources. These provinces should alter talent recruitment policies to attract talent and improve talent utilisation practices, and systems for leveraging and promoting talent in various industries require further development. Regarding Slack_ln3 (welfare resources), Yunnan has the greatest need for improvement, with 35% of its resources being inappropriately applied, followed by Guizhou and Hubei, where welfare resource efficiency could be improved by approximately 30%.

Analysis of output deficiencies

Output deficiencies occur when an economy's production or output of goods and services falls short of potential (Li et al. 2007). This can frequently result in the underutilisation of resources, unemployment and slower economic growth. The eastern region is on par with the central and western regions in terms of employment and urbanization, with central and western regions having more room for improvement in employment and urbanization. On top of the original output, no output deficiencies are evident for GDP values. Labor productivity output (Slack_Ou2) can be increased by 30.01% and the urbanization rate (Slack_ou3) by 18.1%. There is also room for improvement in the central region, where labor productivity output (Slack_Ou2) can rise by 30.35% and urbanization rate (Slack_Ou3) by 27.73%. In the eastern region, it is also essential to increase of days of air quality equal to or above grade II (day) (Slack_Ou4) and forest coverage (Slack_Ou5), as another 1.24% and 12.47% of work can be done, respectively, compared with the central and western regions (Table 7).

Table 7

Output slack value and redundancy rate in 2021 by region

District	Provinces	Slack_ Ou1	Redundancy rate, %	Slack_Ou2	Redundancy rate, %	Slack_Ou3	Redundancy rate, %
Western region	Qinghai	0	0	0	0	0	0
	Tibet	0	0	0	0	0	0
	Sichuan	0	0	342,938.23	125.22	72.41	83.93
	Yunnan	0	0	35,833.4	48.18	24.59	24.67
	Chongqing	0	0	0	0	0	0
	Guizhou	0	0	1,872.47	7.17	3.89	0
Average		0	0	63,440.69	30.1	16.82	18.1
Central region	Hubei	0	0	150,727.25	91.05	58.34	83.18
	Hunan	0	0	0	0	0	0
	Jiangxi	0	0	0	0	0	0
Average		0	0	50,242.42	30.35	19.45	27.73
Eastern region	Anhui	0	0	0	74.61	44.32	38.91
	Jiangsu	0	0	0	0	0	0
	Shanghai	0	0	0	0	0	0
Average		0	0	0	24.87	14.77	12.97

(Table continues on the next page.)

(Continued.)

District	Provinces	Slack_Ou4	Redundancy rate, %	Slack_Ou5	Redundancy rate, %
Western region	Qinghai	0	0	0	0
	Tibet	0	0	0	0
	Sichuan	251.21	0	0	23.42
	Yunnan	88.23	0	0	15.39
	Chongqing	0	0	0	0
	Guizhou	0	0	0	0
Average		56.57	0	0	6.47
Central region	Hubei	239.83	0	0	0
	Hunan	0	0	0	0
	Jiangxi	0	0	0	0
Average		79.94	0	0	0
Eastern region	Anhui	122.13	3.73	1.07	37.42
	Jiangsu	0	0	0	0
	Shanghai	0	0	0	0
Average		40.71	1.24	0.36	12.47

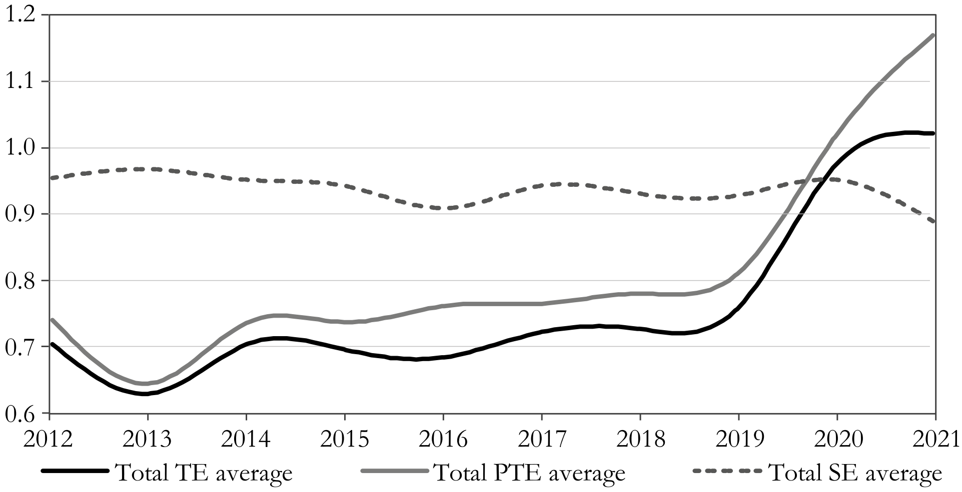
Source: authors' calculations based on model results.

Robustness test

We use the super-efficiency SBM model as a robustness test for the DEA–SBM standard efficiency, allowing for a more thorough examination of DMU performance than binary classifications of efficient/inefficient. The super-efficiency SBM model can also rank efficient DMUs, which is not possible with the standard SBM model as all efficient DMUs are assigned a score of 1. Super-efficiency SBM provides useful information about the stability and reliability of efficiency scores, ensuring that efficiency assessments are accurate and meaningful. We employ this model to simulate the sample data and obtain a high-quality estimate of each province's economic efficiency under the super-efficient model (Zhu 2001). The distribution of super-efficiency in the Yangtze River region is flat compared with standard efficiency; however, the trends are similar, and provinces' resource allocation and management gradually improve over time (Figure 6). Consequently, low standard efficiency is a problem for Sichuan and Hubei, as is their super-economic efficiency. Sichuan finished last in pure technical and technical efficiency. Chongqing, which is close to Sichuan, performs well and ranks second in pure technical and technical efficiency. This indicates that government management in the province is adequate. Tibet's top rank in this efficiency measurement can also be attributed to the benefits derived from natural resources and the environment, which yields many points for economic efficiency output. However, Tibet's scale efficiency is not better than other provinces', indicating the need for improved governance and management. Shanghai's technical and pure technical efficiency are ranked at 3; however, policy implementation in the province is insufficient because big cities do not implement policies equally well (Figure 7).

Figure 6

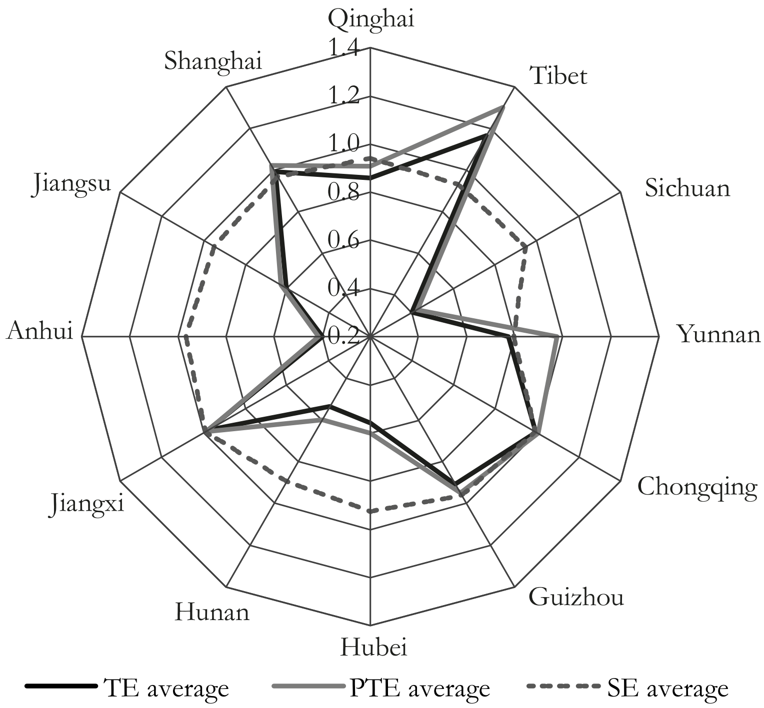
Super-efficiency in the Yangtze River region by time



Source: authors' construction based on model results using Origin 2021 software.

Figure 7

Super-efficiency in the Yangtze River region



Source: authors' construction based on model results using Origin 2021 software.

Discussion

This study examines high-quality economic efficiency using the results of the data analysed with the model described. By evaluating the efficiency of economic development in each region, based on the indices outlined in *China's 14th Five-Year Plan Guidance* for high-quality economic development, we investigate the validity of the assumptions.

Efficiency grows every year but performance in developed regions is poor

The *first part of Assumption 1 does not correspond to the original assumption. Each region's development increases annually; however, the high-quality efficiencies in developed regions are not higher than those in less developed ones. High-quality efficiency* and *pure technology efficiency* exhibit overall upwards trends, but also drop during a particular period. This result differs slightly from previous studies (Zhang et al. 2021) indicating that efficiencies increase every year. The Yangtze River region has exhibited a general trend of improving economic efficiency but fell back in 2013 and 2020. The rationale behind this can be attributed to three factors.

(1) The international economic environment appears to have had a significant impact on the regional economy. In 2013, global industrial production and trade were weak, prices declined, international financial markets were volatile and global economic growth continued to fall slightly. In 2020, the Covid-19 pandemic restrained economic activities.

(2) Traditional manufacturing industries were experiencing downwards pressure. There are many factories in the Yangtze River region. When the economy undergoes transformation, traditional manufacturing facilities come under increased pressure to adjust and upgrade, green and sustainable development regulations constrain conventional industries' development and policy requirements for pollutant emissions can hamper production.

(3) While prudent fiscal policy has reduced regional investments and scaled back infrastructure development efforts, economic efficiency rebounded quickly following the shocks. Therefore, the region's economy has become more resilient. Furthermore, *scale efficiency* fluctuated around a value of 0.9. Stable scale efficiency indicates a certain level of managerial competence, operational consistency and strategic alignment within the organizations. This implies that the Yangtze River region has established a balance of operational efficiency within its current scale without significant opportunities for improvement through alterations to size or scope.

In contrast to *the last part of Assumption 1,* high-quality efficiency in regions with high economic development is not more significant than that in less developed regions, indicating no direct correlation between economic development and high-quality efficiency. This *novel discovery* challenges earlier research findings (Zhang et al. 2021).

Environmental pollution (emission of exhaust gases and other airborne pollutants) is an undesired output in the model with a negative impact on efficiency. Core provinces such as Sichuan and Wuhan have lower economic efficiency values than other regions. Since these two provinces are heavily industrialized, they emit considerable pollutants from industrial production, garnering relatively lower scores than other regions. Environmental pollution reduces provinces' economic efficiency values with high per capita GDP for three reasons.

(1) Environmental pollution affects individual and public health, compelling residents to use more medical resources and experience social limitations.

(2) Combatting environmental damage caused by the discharge of wastewater and waste materials requires enormous financial resources from the government, which makes using resources expensive.

(3) Transforming and upgrading the industrial structure in these provinces is a challenge. Closing traditional manufacturing plants would lead to a short-term decline in productivity in core areas and the establishment of new sustainable and innovative enterprises will require significant financial resources.

Eastern regions benefit more

The findings for *Assumption 2* concerning *input resource distributions* align with many conclusions drawn by the relevant literature sources (Zhang et al. 2021). Numerous factors such as previous development trends, investments in infrastructure and government policies that have historically favored eastern regions can be attributed to this disparity. Out of the four provinces with low efficiency data, the western provinces are more inefficient than the central or eastern provinces.

In terms of *input redundancy* for each region, the superiority of natural geographical location, resource endowment and the speed of human economic development can significantly influence resource utilization rates (Liu et al. 2019). The eastern region has a long history and culture with abundant human resources; therefore, subsequent resource utilization is more efficient and welfare resources are adequate. In contrast, the western region has a higher redundancy rate because of its outlying location and fewer human resources.

According to the *efficiency evaluation system*, from the perspective of regional coordination, differences in efficiency are evident between the eastern and western regions and between core provinces and non-core cities. The relatively underdeveloped educational system in the western region has resulted in a shortage of innovative human resources in science and technology. Because of the higher populations in large cities, resource allocation is insufficient; therefore, the eastern regions have experienced more notable economic growth and development compared with their western counterparts.

The western region has less pollution output than the eastern region

Assumption 3 aligns with common sense. Low pollution is primarily attributable to underdeveloped economic conditions caused by inefficient resource use. Industrial activity is typically limited in areas with slower economic growth, resulting in less environmental harm; however, this is rarely attributable to explicit environmental regulations, but to the fact that particular areas have not fully leveraged existing natural resources due to a lack of infrastructure, technology and/or funding. As a result, although pollution appears to be low, these regions actually reflect economic underperformance rather than long-term growth. The western region has more room for output growth. Regional economic disparities in China have been the subject of numerous studies, many of which have focused on concerns including underproduction, poorer productivity, higher unemployment rates and lower industrial output, particularly in areas with lower economic development (Zhang et al. 2021). Output deficiencies in economically disadvantaged areas are the result of unequal resource allocation and distribution (Quan Liang–Zhao 2019). It is possible that western regions will require more funding, advanced technology, trained workers and better infrastructure to overcome deficits. Its potential output is limited by the absence or scarcity of such resources, suggesting a significant amount of space for output growth in the region.

Summary and conclusions

Using an improved PCA–SBM model, this study analyses and quantifies the major factors driving China's transition to a high-quality economic model employing the example of the Yangtze River region. As the most crucial regional unit, this region offers a mesocosm for investigating a wide range of policy-related, social, environmental and economic issues. This approach moves from mesoeconomic to macroeconomic perspectives; from smaller-scale economic phenomena to a broader and aggregate view of the economy. The proposed methodological and modelling framework can be extended to investigate other regions in China or any other country. High-quality development has been one of the most often investigated topics of China's new economic transformation, focusing on many components, particularly technology and the environment, rather than just one factor that characterized previous economic reforms.

The most crucial *methodological scientific novelty and innovative element* of this study is combining an input–output model with the PCA–SBM composite model and establishing a new index system for evaluating regions' status in moving towards a high-quality economic trajectory based on an efficiency model. The PCA–SBM composite model incorporated innovation, technology, labor and welfare resources as input indicators, and labor productivity and environmental pollution as output indicators. The results provide a descriptive analysis and visual graphs illustrating changes over time and regional specificities.

The most novel finding is that *high-quality efficiency*, *pure technology efficiency* and *scale efficiency* only occasionally tend to grow annually. They are frequently influenced by external factors (i.e. the Covid-19 pandemic), and return to potential trend lines following disruptions, presenting a long-term upwards trend in regional economic development.

Another significant finding is that no direct correlation is evident between economic development and high-quality efficiency. This is a *novel discovery* that challenges earlier research findings (Zhang et al. 2021). High economic development differs from the high-quality economy transition primarily because environmental pollution is one metric of the current evaluation.

According to the *input redundancy analysis*, developed core provinces scored low, indicating that Sichuan Province (a more developed area in the western region) has fewer good air quality days and a lower green ecology score, giving it the lowest efficiency rating. Concerning critical pollution emissions, an economy with a high GDP per capita and a high degree of urbanization seems less valuable.

The *efficiency evaluation system* developed from the perspective of regional coordination also reveals differences in efficiency between the eastern and western regions and between core provinces and non-core cities. *Input resource deficiencies* correlate with economic development, and western regions have more room to improve output.

According to previous research, resource distribution remains uneven, resulting in regional disparities. Disparities persist in access to quality education and healthcare services across regions and constitute a complex and ongoing challenge in China.

Considering the results, the following four policy measures could be taken:

(1) *Environmental protection:* To achieve a positive interaction between economic development and environmental protection in the Yangtze River region, pollution and waste emissions must be reduced, the production and the diffusion of clean energy should be promoted and activities such as ecological restoration and environmental protection should be conducted.

(2) *Industrial upgrading:* New and high-tech industries should be developed in the Yangtze River region, the technological and value-added content of the region's economic structure should be improved and industrial innovation capacity and enterprise competitiveness must be enhanced. Therefore, it is essential to accelerate the economic transformation of traditional industrial provinces to upgrade industrial structures.

(3) *Education and talent cultivation:* The western region should receive more preferential education and social welfare treatment. Therefore, higher education and vocational training should be strengthened to meet economic transformation needs in the Yangtze River region.

(4) *Policy support:* The Yangtze River region should increase policy support, promote investment and entrepreneurship, optimize its business environment, reduce business costs and improve economic development dynamics.

In summary, to achieve a high-quality economy in the Yangtze River region, efforts must be undertaken to prioritize environmental protection, industrial upgrading, talent nurturing, policy support and coordinated regional development. Only through a comprehensive and coordinated approach can the Yangtze River region's economy be developed in a high-quality manner.

Notably, *this study also has some limitations.* Referencing on the 14th Five-Year Plan, we only select valid and representative indicators for efficiency assessment. Consequently, other factors and types of data should be included. We used 120 samples in this paper for our macroeconomic efficiency analysis, and this number should be increased. Another limitation of the model is the loss of data when reducing the indicators' dimensionality, which results in incomplete figures. Therefore, as a future research direction, we will transition from examining provincial economic efficiency to analyzing urban economic efficiency, which will enable us to analyze the nature of economic growth in each urban area.

Appendix

Table A1

Indicator definitions

Group	Indicators	Definition
Innovation-driven indicators	R&D spending of industrial enterprises above the scale (10,000 yuan)	The annual main business income of 20 million yuan and above the funding of research and experimental development projects of legal industrial enterprises.
	The number of domestic invention patent applications received (items)	Invention (patent) refers to a new technical solution proposed for a product, method or its improvement. It is an internationally accepted core indicator reflecting the possession of independent intellectual property rights technology.
	Revenue from software business (100 million yuan)	The revenue from commercial activity of the software industry, aimed at producing, buying and selling software products or software services.
Safety & security indicators	Overall grain production capacity (hundreds of million tons)	The total amount of food produced during the calendar year.
People's welfare indicators	The disposable income growth per capita (%)	Disposable income is the sum of final consumption expenditure and savings available to residents, i.e., the income available to residents for discretionary purposes, including both cash and in-kind income.
	Surveyed urban unemployment (1,000 person)	The unemployed population is defined as people 16 years of age and older who are not working but have been actively looking for work in the last 3 months and would be able to start working within 2 weeks if a suitable job became available.
	The number of certified (assistance) doctors (1,000 persons)	The "level" of the "Certified Assistant Physician" and actually engaged in medical, preventive health care work personnel.
	Number of urban and rural residents' social old-age insurance participants (10,000)	The people who participant a social pension insurance system that combines individual contributions, collective subsidies and government subsidies to guarantee the basic livelihood of rural residents and urban residents in their old age.
	Average number of nursery school students per 100,000 population (persons)	This refers to the average number of students per 100,000 population in a given school year including all levels of schooling.
Economic development Indicators	Reginal gross domestic products (CNY 100 million)	It is the final result of production activities of all resident units in the region in a certain period of time. Reginal gross domestic products is equal to the sum of the value added of each industry.
	Workforce productivity (Yuan/1person)	Refers to the labor efficiency of all workers (employees) in society in a certain period of time.
	Urbanization rate (%)	The urbanization rate refers to the proportion of the resident population in cities and towns of a country (region) to the total population of that country (region), and is an important indicator to measure the high level of urbanization and reflect the urbanization process.
Green ecology indicators	Days of air quality equal to or above grade II (day)	Air quality index within 100 is considered the quality of air is above II.
	Forest coverage rate	Forest cover is the amount of trees that covers a particular area of land. It may be measured as relative (in percent).
	Emission of exhaust gas (10,000 tons)	Combined emissions of various pollutant gases into the air.

Sources: ADB 2021.

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