ISSN: 2029-4913 / eISSN: 2029-4921

VILNIUS TECH
Vilnius Gediminas Technical University

TECHNOLOGICAL and ECONOMIC DEVELOPMENT of ECONOMY

2026
Volume 32
Issue 2
Pages 485–507
https://doi.org/10.3846/tede.2025.24894

EFFICIENCY AND REGIONAL DIVERGENCE IN CHINA'S POVERTY REDUCTION (SDG 1) AND DECENT WORK AND ECONOMIC GROWTH (SDG 8)

Li JI[1], Shigui TAO[1], Tai-Yu LIN[2], Yanan SUN[3],
Mingle CHEN[4], Yung-ho CHIU[5]✉, Wesley HU[6]

[1] *School of Business, Nanjing Normal University, Jiangsu, China*
[2] *Department of Business Administration, National Cheng Kung University, Tainan City, Taiwan*
[3] *School of Business, Nantong University, Jiangsu, China*
[4] *School of business, Xi'an Jiaotong-Liverpool University, Jiangsu, China*
[5] *Department of Economics, Soochow University, Taipei, Taiwan*
[6] *Lexington High School, Lexington, Massachusetts, United States*

Article History:
- received 27 December 2024
- accepted 12 September 2025
- first pubished online 29 October 2025

Abstract. Addressing regional disparities while pursuing sustainable development has become a critical policy challenge. This study develops a meta parallel two-stage dynamic range directional measure (RDM) directional distance function (DDF) data envelopment analysis (DEA) model to evaluate the efficiency of poverty reduction (SDG 1) and decent work and economic growth (SDG 8) across 30 provinces in China. Given uneven regional development, the provinces are grouped into eastern, central, and western regions, and kernel density estimation is employed to examine the spatial and temporal evolution of efficiency. The results indicate that: (1) The overall efficiency is moderate, with an average score of 0.67, highest in the eastern region, followed by the western, and lowest in the central region. (2) The efficiency of SDG 8 (0.93) significantly exceeds that of SDG 1 (0.87), while the regional ranking remains consistent with the overall efficiency. (3) The technology gap among the three regions shows dynamic changes: the western region has overtaken the eastern region to become the most advanced. In contrast, the central region continues to lag, and its gap with the other regions is steadily widening.

Keywords: poverty reduction, decent work and economic growth, sustainable development, dynamic RDM-DDF DEA model.

JEL Classification: D31, J13, O11.

✉Corresponding author. E-mail: *echiu@scu.edu.tw*

1. Introduction

Poverty is a major barrier to economic development and a core expression of social inequality. The United Nations Sustainable Development Goals (SDGs) highlight poverty reduction (SDG 1) and decent work and economic growth (SDG 8) as central objectives, underscoring their close interconnection. Theoretically, economic growth reduces poverty reduction by creating employment opportunities (Aghion & Bolton, 1997), while poverty reduction fosters growth by improving human capital and stimulating consumer demand (Ravallion, 2001). The poverty-reducing effect of economic growth depends on labor market structure, job quality, and income distribution equity (Bourguignon, 2003). If economic growth fails to create sufficient jobs, or if job quality remains poor, marked by informal employment or stagnant wages, its impact on poverty reduction is greatly weakened (Kapsos, 2005). Therefore, poverty reduction must be evaluated alongside decent work and economic growth. Assessing sustainable growth requires determining whether its benefits reach low-income groups.

Over the past four decades, China has maintained an average annual GDP growth above 8%, lifting over 700 million people out of poverty and achieving notable progress in both economic development and poverty reduction. Now, poverty has shifted from "survival-based" to "development-oriented," marked by employment instability, skill mismatches, and widening urban-rural income gaps. As poverty declines and the economy shifts toward high-quality growth, improving labor market efficiency and inclusiveness emerges as a critical challenge. Consolidating and expanding poverty reduction gains while sustaining economic growth is vital not only to China's long-term prosperity but also to offering insights for other countries advancing sustainable development.

Existing research reveals three limitations. First, most studies examine poverty reduction or economic growth separately, rarely integrating poverty, employment, and growth to capture their dynamic interactions (Caminada & Goudswaard, 2009; Duan et al., 2022). Second, conventional econometric models inadequately reflect the dynamic evolution of interregional technological disparities, particularly the pronounced gaps among eastern, central, and western China (Färe et al., 2007; Shahbaz et al., 2022). Third, the selection of variables is often simplistic. Poverty reduction is measured by the proportion of the population lifted out of poverty, overlooking social security and living standards (Kerr et al., 2017; Hogendoorn et al., 2020). Similarly, employment is proxied by job or unemployment rates, neglecting employment structure and sectoral distribution (Friedberg et al., 2018; Kroft & Notowidigdo, 2016).

The main contributions of this paper are as follows: 1. Theoretically, it bridges the analytical gap between SGD 1 and SDG 8 by proposing an integrated framework that highlights China's poverty alleviation strategy. 2. Methodologically, it develops a meta parallel two-stage dynamic RDM-DDF DEA model that integrates SDG 1 and SDG 8 into a unified framework. The RDM component resolves infeasibility caused by negative values, while the dynamic feature enables intertemporal provincial comparisons, addressing the limitations of static DEA models. 3. In terms of variable construction, the study employs multidimensional indicators including average life expectancy, the base of minimum living allowance for residents, the proportion of employees in high-tech enterprise, cultural and financial industries, and the educational composition of the labor force. These measures offer a more comprehensive evaluation of the performance of SDG 1 and SDG 8. 4. Kernel density estimation reveals increasing regional polarization, underscoring the need for region-specific policy interventions.

2. Literature review

2.1. Poverty reduction, decent work, and economic growth

Theoretical perspectives on poverty governance have shifted from a one-dimensional economic focus to a multidimensional framework. Sen's (2020) capability approach marked a turning point income-based definitions of poverty, providing the theoretical basis for linking SDG 1 with SDG 8. Kuznets (2019) advanced the inverted U hypothesis, suggesting that economic growth initially exacerbates inequality and poverty. Empirical studies (Ravallion, 1995; Adams, 2004) confirmed the positive impact of growth on poverty reduction, particularly when it generates sufficient, high-quality employment (Kapsos, 2005; Wang et al., 2024). Hangoma and Surgey (2019) emphasized that poverty reduction is central to the SDGs and depends on inclusive access to decent work. Similarly, Menton et al. (2020) argued that employment expansion and sustained growth foster sustainable development and are essential for poverty reduction. Using Jordan as a case study, AlBataineh (2024) found that remittances positively affect both economic growth and poverty reduction.

Since the 1990s, China has advanced poverty reduction through institutional reforms and targeted interventions. Key measures include improving resource allocation (Zhang et al., 2017) and relocating impoverished populations in remote areas (Zhou et al., 2020). Wan et al. (2021) showed that expanding job opportunities and providing training for vulnerable groups markedly reduce poverty, while Zhang et al. (2022) emphasized that SDG 1 and SDG 8 remain central to China's social development across economic cycles.

2.2. The development of DEA model

Chung et al. (1997) extended the introduced the DDF DEA model by introducing the output-oriented distance function. Since traditional DDF, often overestimates efficiency, Färe and Grosskopf (2010) proposed a non-radial DDF model to improve accuracy. To capture hierarchical decision-making, Färe and Grosskopf (2000) developed single and two-level structures for evaluating decision-making units (DMUs) composed of sequential or parallel sub-units. Further, Färe et al. (2007) developed Network DEA, incorporating input allocation and intermediate products to overcome the limitations of the traditional "black box" approach.

A fundamental network structure is the parallel system, where a DMU consists of multiple sub-units. Kao (2009) analyzed the link between component inefficiencies and overall performance, proposing a parallel DEA model to evaluate efficiencies at both the system and component levels. Since economic entities such as countries or firms operate across multiple periods. To assess both cross-sectional and temporal efficiency, dynamic DEA is needed, requiring integration with network DEA. Addressing this, Tone and Tsutsui (2014) proposed the dynamic network DEA model. However, existing studies have yet to account for both cross-period persistence and parallel subsystems, nor have they fully incorporated heterogeneous technologies or variables that take negative values. This study seeks to address three critical limitations in existing DEA frameworks: (1) Cross-period dynamics, such as lagged effects of poverty reduction; (2) Subsystem parallelism, such as the synergy between employment and poverty alleviation; (3) The non-negativity constraint, as some economic or employment indicators may take negative values.

2.3. Literature gaps

China's rapid economic progress, poverty reduction, and employment have attracted global attention. Assessing the efficiency of SDG 1 and SDG 8 in the Chinese context addresses a critical gap in the literature and offers both theoretical insights and practical guidance for countries striving to achieve the 2030 SDGs.

Most studies focus on individual components or examine the link between poverty alleviation and economic growth. Research integrating SDG 1 and SDG 8 into a unified analytical framework is still limited. However, the potential synergistic between these goals and their joint contribution to sustainable development are evident, warranting further investigation. Moreover, traditional DEA models cannot handle negative value inputs, such as GDP and population growth rates. Existing studies on SDG efficiency often overlook interactions among goals. Considering China's vast territory and regional disparities in resources, development stages, and SDG performance, a regional study is necessary.

3. Research methods

This paper develops a meta parallel two-stage dynamic RDM-DDF DEA model. The RDM model proposed by Portela et al. (2004) is employed to address negative variables, and the parallel two-stage structure captures interactions between SDG 1 and SDG 8. To assess technological gaps across eastern, central, and western regions, meta-frontier analysis (O'Donnell et al., 2008) is applied. Furthermore, kernel density estimation is used to analyze the spatiotemporal evolution of efficiency.

3.1. Stages and input-output variables

The DEA model consists of two stages. The first stage representing government investment. The second stage includes two parallel sub-stages (stage 2.1 and stage 2.2). Stage 2.1 focuses on SDG 1 (SDG 1.2, 1.3, 1.4), stage 2.2 focuses on SDG 8 (SDG 8.1, 8.2, 8.3, 8.6, 8.9, 8.10). The relevant variables are in Table 1. Figure 1 illustrates the research framework.

3.2. Entropy methodology and steps

Each stage involves multiple input and output variables. The entropy method (Shannon, 1948) is applied to address potential inefficiency caused by an excessive number of variables, thereby improving the accuracy of efficiency estimation.

Step 1: The data is normalized through range standardization.

$$r_{mn} = \frac{\max_m x_{mn} - x_{mn}}{\max_m x_{mn} - \min_m x_{mn}}, \ m = 1, ..., 30, \ n = 1, ..., N. \tag{1}$$

where r_{mn} is the standardized value of the n^{th} indicator for the m^{th} province, $\min_m x_{mn}$ is the minimum value of the n^{th} indicator for the m^{th} province, and $\max_m x_{mn}$ is the maximum value of the n^{th} indicator for the m^{th} province.

Step 2: Calculate the proportion of each indicator.

$$P_{mn} = \frac{R_{mn}}{\sum_{m=1}^{30} R_{mn}}. \tag{2}$$

P_{mn} represents the proportion of the m^{th} evaluation object on the n^{th} variable, where m is the total number of evaluation objects.

Table 1. The variables of the model

Stage	Item	Variable	
Stage 1	Inputs	*Expenditure for social safety net and employment effort* (*SSE*)	
		Expenditure for environment protection (*EP*)	
		Expenditure for social Comprehensive (*SC*)	*Education; Medical and health care; Transportation*
	Desirable outputs (Link)	*Infrastructure index* (*II*)	*Per capita urban road area; Per capita park area*
		Social service indicator (*SSI*)	*Natural population growth rate; Average life expectancy; Average educational year; Proportion of people in higher education*
	Undesirable output		*Crime rate* (*CR*)
Stage 2.1	Outputs	*No poverty indicator* (*NPI*)	*Percentage of people not living in poverty; Base of minimum living allowance for residents*
		Nature gas penetration rate (*GPR*)	
Stage 2.2	Outputs	*Decent work* (*DW*)	*Proportion of employees in high-tech enterprise; Proportion of employees with college degree or above; Proportion of employment in cultural industries; Proportion of employment in financial industries*
		Employment rate (*ER*)	
		GDP growth rate (*GGR*)	
Carry-over		Fixed assets	

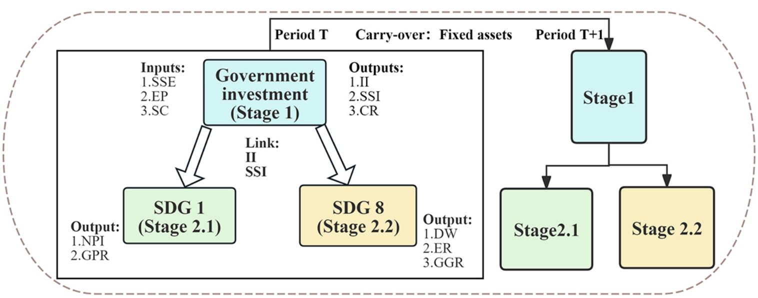

Figure 1. The research framework

Step 3: Calculate the entropy value of the n^{th} indicator (e_n).

$$e_n = -k\sum_{m=1}^{30}\left[P_{mn}\ln\left(P_{mn}\right)\right],\ k = \frac{1}{\ln m}. \tag{3}$$

e_n represents the entropy equation. If the proportion P_{mn} for any indicator is 0, then $P_{mn}\ln\left(P_{mn}\right)$ is defined as 0.

Step 4: Calculate the weight of each variable.

$$w_n = \frac{1-e_n}{\sum_{n=1}^{N}\left(1-e_n\right)}. \tag{4}$$

N represents the total number of variables, and the weigh w_n indicates the importance of indicator n. The term $1 - e_n$ represents the difference coefficient, with a larger $1 - e_n$ indicating a greater weight of the variable.

3.3. A meta parallel two-stage dynamic RDM-DDF DEA model

DMUs on the efficiency frontier select the most favorable weighted output. Accordingly, the efficiency of public-boundary DMUs is determined using the following linear programming model, which calculates total efficiency, period efficiency, stage efficiency, and period-stage efficiency for each DMU.

Suppose there are two stages in each t time period (t = 1, ..., T): Stage 1 and Stage 2. Stage 2 is further divided into Stage 2.1 and Stage 2.2. Each DMU on the efficiency frontier selects the most favorable weighted outputs. The relevant variables and expressions are presented in Table 2.

Table 2. The expression of variable

Stage	Item	Variable	Expression
Stage 1	Input	*SSE, EP, SC*	$f_{bj}^{t}\left(b=1,\ldots,B\right)$
	Desirable output	*II, SSI*	$q_{aj}^{t}\left(a=1,\ldots,A\right)$
	Undesirable output	CR	$U_{oj}^{t}\left(o=1,\ldots,O\right)$
Stage 2.1	Link	*II, SSI*	$z_{hj}^{t}\left(h=1\ldots H\right)/\,x1_{ij}^{t}\left(i=1,\ldots,I\right)$
	Output	*NPI, GPR*	$y1_{kj}^{t}\left(k=1,\ldots,K\right)$
Stage 2.2	Link/Input	*II, SSI*	$w_{vj}^{t}\left(v=1,\ldots,V\right)/\,x2_{dj}^{t}\left(d=1,\ldots,D\right)$
	Output	*DW, ER, GGR*	$y2_{sj}^{t}\left(s=1,\ldots,S\right)$
Carry-over		*Fixed assets*	$c_{lj}^{t}\left(l=1,\ldots,L\right)$

3.3.1. Meta Frontier (MF)

Due to differences in management type, resources, regulations, or environment, all firms N (j = 1 ... N) are composed of g groups of DMUs under a common boundary $\left(N=N_1+N_2+\ldots+N_G\right)$. Therefore, the efficiency of DMU j under the common boundary can be solved by the following linear programming procedure. The DMU efficiency under the MF is $\max MFE=\sum_{g=1}^{G}\sum_{t=1}^{T}\left(w_{g1}^{t}\theta_{g1}^{t}+w_{g2}^{t}\theta_{g2}^{t}\right)$, t = 1, 2, ..., T, and the model structure of DMU efficiency under the MF in Table 3.

The link of two periods: $\sum_{g=1}^{G}\sum_{j=1}^{n}\lambda_j^{t-1}c_{lj}^{t}=\sum_{g=1}^{G}\sum_{j=1}^{n}\lambda_j^{t}c_{lj}^{t},\ \forall l,\forall t.$

$R_{bp1}^{t}, R_{ap1}^{t}, R_{op1}^{t}$ denote the direction vectors associated with stage 1 inputs, desirable output, undesirable output. $R_{bp1}^{t}=f_{bp1}^{t}-\min_j\left(f_{bj1}^{t}\right)$, $R_{ap1}^{t}=\max_j\left(q_{aj1}^{t}\right)-q_{ap1}^{t}$, $R_{op1}^{t}=U_{op1}^{t}-\min_j\left(U_{oj1}^{t}\right)$, $R_{ip2.1}^{t}$, $R_{kp2.1}^{t}$ denote the direction vectors associated with stage 2.1 inputs, desirable output;

Table 3. Model structure of the DMU efficiency under MF

Stage 1	Stage 2.1
$\sum_{g=1}^{G}\sum_{j}^{n}\lambda_{gj1}^{t} f_{gbj1}^{t} \le f_{gbp1}^{t} - \theta_{g1}^{t} R_{gbp1}^{t},\ \forall b$	$\sum_{g=1}^{G}\sum_{j}^{n}\lambda_{gj2.1}^{t} X1_{gij2.1}^{t} \le X1_{gip2.1}^{t} - \theta_{g2.1}^{t} R_{gip2.1}^{t}, \forall i$
$\sum_{g=1}^{G}\sum_{j}^{n}\lambda_{gj1}^{t} q_{gaj1}^{t} \ge q_{gap1}^{t} + \theta_{g1}^{t} R_{gap1}^{t},\ \forall a$	$\sum_{g=1}^{G}\sum_{j}^{n}\lambda_{gj2.1}^{t} y1_{gkj2.1}^{t} \ge y1_{gkp2.1}^{t} + \theta_{g2.1}^{t} R_{gkp2.1}^{t},\ \forall k$
$\sum_{g=1}^{G}\sum_{j}^{n}\lambda_{gj1}^{t} U_{goj1}^{t} \le U_{gop1}^{t} - \theta_{g1}^{t} R_{gop1}^{t},\ \forall o$	$\sum_{g=1}^{G}\sum_{j}^{n}\lambda_{gj1}^{t} z_{ghj(1,2.1)}^{t} \ge z_{ghp(1,2.1)}^{t} + \theta_{g2.1}^{t} R_{ghp(1,2.1)}^{t},\ \forall h$
$\sum_{g=1}^{G}\sum_{j}^{n}\lambda_{gj1}^{t} = 1\ \ \lambda_{gj1}^{t} \ge 0,\ \forall j$	$\sum_{g=1}^{G}\sum_{j}^{n}\lambda_{gj2.1}^{t} = 1\ \ \lambda_{gj2.1}^{t} \ge 0,\ \forall j$
Stage 2.2	
$\sum_{g=1}^{G}\sum_{j}^{n}\lambda_{gj2.2}^{t} X2_{gdj2.2}^{t} \le X2_{gdp2.2}^{t} - \theta_{g2.2}^{t} R_{gdp2.2}^{t}, \forall d$	$\sum_{g=1}^{G}\sum_{j}^{n}\lambda_{gj2.2}^{t} y2_{gsj2.2}^{t} \ge y2_{gsp2.2}^{t} + \theta_{g2.2}^{t} R_{gsp2.2}^{t},\ \forall s$
$\sum_{g=1}^{G}\sum_{j}^{n}\lambda_{gj2}^{t} w_{gvj(1,2.2)}^{t} \ge w_{gvp(1,2.2)}^{t} + \theta_{g2,2}^{t} R_{gvp(1,2.2)}^{t}, \forall v$	$\sum_{g=1}^{G}\sum_{j}^{n}\lambda_{gj2.2}^{t} = 1\ \ \lambda_{gj2.2}^{t} \ge 0\ , \forall j$

$R_{dp2.2}^{t}$, $R_{sp2.2}^{t}$ denote the direction vectors associated with stage 2.2 inputs, desirable output. $R_{ip2.1}^{t} = X1_{ip2.1}^{t} - \min_{j}\left(X1_{ij2.1}^{t}\right)$, $R_{kp2.1}^{t} = \max_{j}\left(y1_{kj2.1}^{t}\right) - y1_{kp2.1}^{t}$, $R_{dp2.2}^{t} = X2_{dp2.2}^{t} - \min_{j}\left(X2_{dj2.2}^{t}\right)$, $R_{sp2.2}^{t} = \max_{j}\left(y2_{sj2.2}^{t}\right) - y2_{sp2.2}^{t}$. $R_{dp(1,2.1)}^{t}$ denote the link from division 1 to division 2.1, $R_{vp(1,2.2)}^{t}$ denote the link from division 1 to division 2.2. $R_{dp(1,2.1)}^{t} = \max_{j}\left(z_{dj(1,2.1)}^{t}\right) - z_{dp(1,2.1)}^{t}$, $R_{vp(1,2.2)}^{t} = \max_{j}\left(w_{vj(1,2.2)}^{t}\right) - w_{vp(1,2.2)}^{t}$. The weights of stage 1 and Stage 2: w_1^t, w_2^t; The efficiency of stage 1 and stage 2: θ_1^t, θ_2^t .

3.3.2. Group Frontier (GF)

The DMU efficiency under the GF is $\max GFE = \sum_{t=1}^{T}\left(w_1^t\theta_1^t + w_2^t\theta_2^t\right)$, t = 1, 2, ..., T, and the model structure of DMU efficiency under the GF in Table 4.

The link of two periods: $\sum_{j=1}^{n}\lambda_j^{t-1} c_{lj}^{t} = \sum_{j=1}^{n}\lambda_j^{t} c_{lj}^{t}\quad \forall l, \forall t$.

3.4. Technology GAP Ratio (TGR)

The production frontiers of the g groups are incorporated into the meta-frontier. Technical efficiency under the meta-frontier is always less than or equal to that under the group frontiers. The ratio of these two efficiencies is defined as the Technology Gap Ratio (TGR), $TGR = \frac{MFE}{GFE}$. TGR reflects the gap between the group frontier and the meta-frontier. A TGR value closer to 1 indicates that the efficiencies of the group frontier and meta-frontier are similar, while a value closer to 0 suggests a larger disparity between them.

Table 4. Model structure of the DMU efficiency under GF

Stage 1	Stage 2.1
$\sum_{j}^{n} \lambda_{j1}^{t} f_{bj1}^{t} \leq f_{bp1}^{t} - \theta_{1}^{t} R_{bp1}^{t} \ \forall b,$	$\sum_{j}^{n} \lambda_{j2.1}^{t} X1_{ij2.1}^{t} \leq X1_{ip2.1}^{t} - \theta_{2.1}^{t} R_{ip2.1}^{t} \ \forall i$
$\sum_{j}^{n} \lambda_{j1}^{t} q_{aj1}^{t} \geq q_{ap1}^{t} + \theta_{1}^{t} R_{ap1}^{t} \ \forall a$	$\sum_{j}^{n} \lambda_{j2.1}^{t} y1_{kj2.1}^{t} \geq y1_{kp2.1}^{t} + \theta_{2.1}^{t} R_{kp2.1}^{t} \ \forall k$
$\sum_{j}^{n} \lambda_{j1}^{t} U_{oj1}^{t} \leq U_{op1}^{t} - \theta_{1}^{t} R_{op1}^{t} \ \forall o$	$\sum_{j}^{n} \lambda_{j2.1}^{t} = 1, \lambda_{j2.1}^{t} \geq 0 \ \forall j$
$\sum_{j}^{n} \lambda_{j1}^{t} = 1, \lambda_{j1}^{t} \geq 0 \ \forall j$	$\sum_{j}^{n} \lambda_{j1}^{t} z_{hj(1,2.1)}^{t} \geq z_{hp(1,2.1)}^{t} + \theta_{1}^{t} R_{hp(1,2.1)}^{t} \ \forall h$
Stage 2.2	
$\sum_{j}^{n} \lambda_{j2.2}^{t} X2_{dj2.2}^{t} \leq X2_{dp2.2}^{t} - \theta_{2.2}^{t} R_{dp2.2}^{t} \ \forall d$	$\sum_{j}^{n} \lambda_{j2.2}^{t} y2_{sj2.2}^{t} \geq y2_{sp2.2}^{t} + \theta_{2.2}^{t} R_{sp2.2}^{t} \ \forall s$
$\sum_{j}^{n} \lambda_{j2}^{t} w_{vj(1,2.2)}^{t} \geq w_{vp(1,2.2)}^{t} + \theta_{2}^{t} R_{vp(1,2.2)}^{t} \ \forall v$	$\sum_{j}^{n} \lambda_{j2.2}^{t} = 1, \lambda_{j2.2}^{t} \geq 0 \ \forall j$

3.5. Input and output efficiencies

The difference between each DMU's actual input-output values and the target values under optimal efficiency reflects the potential for improvement in both input-output oriented perspectives. In this study, input-output efficiency is measured by the ratio of the actual values target values. $\text{Input efficiency} = \frac{\text{Target input}}{\text{Actual input}}$, $\text{Output efficiency} = \frac{\text{Actual output}}{\text{Target output}}$, $\text{Undesirable output efficiency} = \frac{\text{Target Undesirable output}}{\text{Actual Undesirable output}}$.

3.6. Kernel density analysis

Kernel density analysis is a widely used non-parametric method for characterize the dynamic evolution of variables. It estimates the probability density function of a random variable using a continuous and smooth curve, rather than a discrete histogram. Assuming the density function of random variable X is $f(x)$, $f(x) = \frac{1}{Nh} \sum_{i=1}^{N} K\left(\frac{X_i - x}{h}\right)$, N is the 30 provinces in this study, h is the bandwidth, $K()$ is the kernel function, X_i is the efficiency value of each province, and x is the sample mean.

4. Empirical analysis

4.1. Data description and statistical analysis

These provinces are grouped into eastern, central, and western regions based on their geographical locations, as shown in Table 5. Table 6 presents statistical description.

Table 5. Regional division of China

Region	Province
Eastern	Beijing, Tianjin, Shanghai, Liaoning, Hebei, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong, Hainan
Central	Heilongjiang, Jilin, Henan, Shanxi, Anhui, Hubei, Hunan, Jiangxi
Western	Gansu, Guizhou, Ningxia, Qinghai, Shaanxi, Yunnan, Xinjiang, Sichuan, Chongqing, Guangxi, Inner Mongolia

Table 6. Statistical description of inputs and outputs

Stage	Variable	Unit	Mean	Std	Max	Min
Stage 1	SSE	10^8CNY	817.31	394.91	1998.67	146.23
	EP	10^8CNY	181.48	110.10	747.44	31.54
	SC		883.05	3137.92	14074.15	–2.14
	II		14.72	3.05	23.35	6.20
	SSI		22.78	4.15	42.18	17.33
	CR	%	5.67	2.63	9.97	1.06
Stage 2.1	NPI		474.72	129.89	1007.28	291.30
	GPR	%	95.53	5.01	100.00	75.93
Stage 2.2	DW		7.23	3.78	23.27	2.96
	ER	%	96.81	0.63	98.70	95.40
	GGR	%	7.47	4.02	21.24	–5.34
carry-over	Fixed assets	10^8CNY	21244.39	14428.88	58980.02	2736.29

4.2. Overall efficiency

Figure 2 shows the overall efficiency and rankings. The average efficiency is 0.67, indicating modest performance. The eastern region leads with an efficiency of 0.72, followed by the western region at 0.70, while the central region ranks lowest at 0.57.

Beijing, Tianjin, Shanghai, Shandong, Jiangsu, and Inner Mongolia achieved optimal efficiency, each scoring 1.00. Except for Inner Mongolia, these provinces are located in the eastern coastal region and are feature advanced economies, high openness, and well-developed infrastructure. Provinces with efficiency values between 0.8 and 1.0 include Fujian, Hainan, Anhui, Ningxia, Qinghai, Guangxi, and Guizhou. Those scoring between 0.6 and 0.8 include Shanxi (0.64), Jiangxi (0.78), Gansu (0.76), Yunnan (0.72), and Chongqing (0.65). Twelve provinces scored below 0.6, with particularly low performance in Liaoning, Hebei, and Guangdong (all 0.23), as well as Shaanxi (0.27) and Sichuan (0.18).

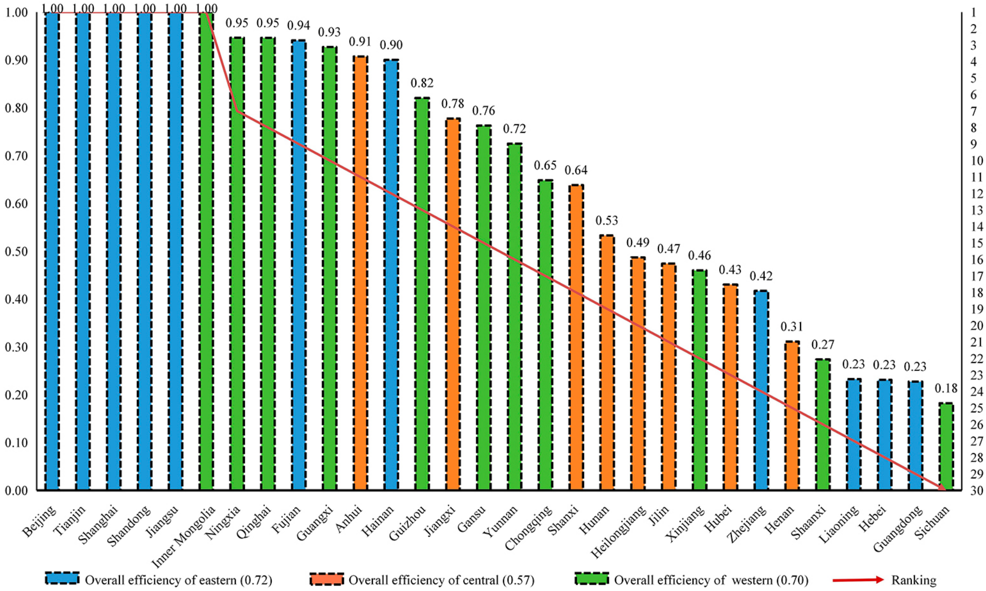

Figure 2. Overall efficiency and ranking of 30 provinces

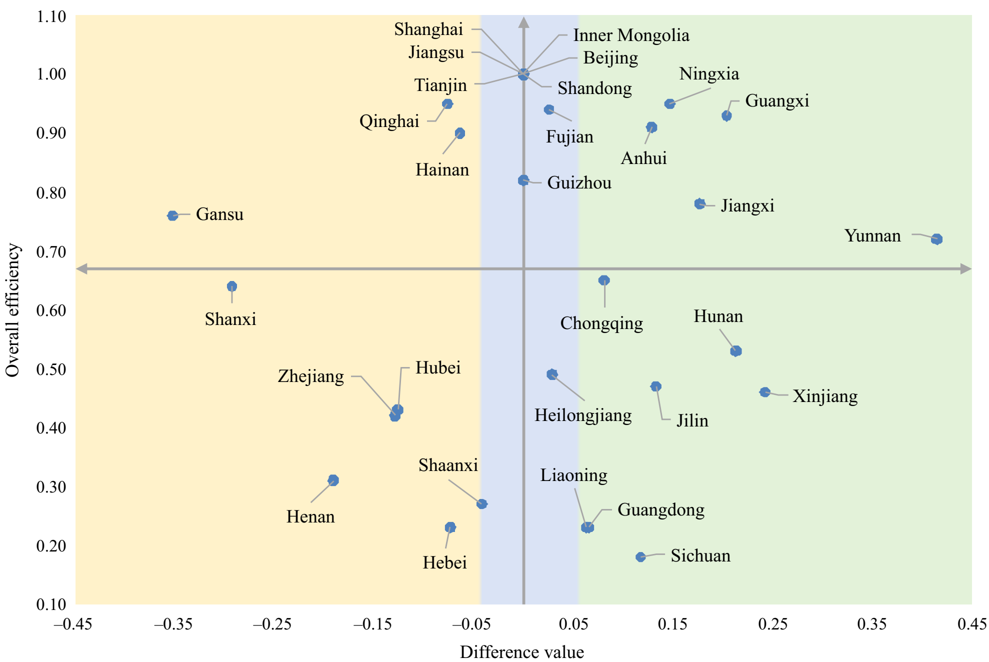

Figure 3. Annual efficiency score trends of overall efficiency

Figure 3 illustrates the fluctuation trends in overall efficiency from 2015 to 2020. The 30 provinces are classified into three groups: decreasing, remaining, and increasing. The X-axis represents the degree of fluctuation, with positions closer to the center indicating greater stability over time. The Y-axis shows overall efficiency, where higher values reflect better performance. The average efficiency score of 0.67 is set as the midpoint of the Y-axis.

Fourteen provinces showed improvements in efficiency, including Sichuan, Liaoning, Guangdong, Xinjiang, Jilin, Heilongjiang, Hunan, Chongqing, Yunnan, Jiangxi, Anhui, Guangxi, Fujian, and Ningxia, with Yunnan showing the most significant gain. Anhui, Guangxi, Fujian, and Ningxia began with efficiency scores above 0.9 and maintained high performance throughout the study period.

Seven provinces maintained relatively stable efficiency and reached optimal levels in 2020. These include Guizhou, Beijing, Tianjin, Shanghai, Shandong, Jiangsu, and Inner Mongolia. Over the long term, they have exhibited consistently high efficiency and are mostly located in the eastern region.

Nine provinces experienced a decline in efficiency over the study period. Hainan and Qinghai began with high initial scores but showed a gradual decrease. Gansu and Shanxi recorded the most substantial declines. These provinces should adopt timely macroeconomic measures to prevent further deterioration in efficiency.

4.3. Government investment efficiency

Table 7 reports government investment efficiency, with an average score of 0.77. The western region leads at 0.81, followed by the eastern region at 0.76 and the central region at 0.73, indicating slightly weaker performance. Over time, efficiency increased from 2015 to 2017 but declined between 2017 and 2020.

The western region performed well in government investment efficiency. Ningxia, Qinghai, and Inner Mongolia rank highest, each with an average efficiency of 1. Gansu, Xinjiang, and Guangxi form the second tier, with scores ranging from 0.9 to 1. Guizhou and Yunnan fall within the 0.8–0.9 range. In contrast, Shaanxi and Sichuan show weaker performance, with values of 0.37 and 0.23, respectively. Over the study period, Yunnan, Xinjiang, and Guangxi improved, with Yunnan achieving the largest increase, from 0.56 in 2015 to 1.00 in 2020. Gansu, conversely, experienced the sharpest decline, falling from 1.00 to 0.52 over the same period.

Government investment efficiency in the eastern region is moderate, although several provinces perform exceptionally well. Beijing, Tianjin, Shanghai, Shandong, Jiangsu, and Fujian maintained optimal efficiency (1.00) from 2015 to 2020. These provinces play a central role in China's economy, benefiting from large economic scale, strategic location, advanced industrial structure, and strong innovation capacity. Hainan follows closely with a slightly lower efficiency of 0.99. Provinces with efficiency below 0.5 include Liaoning, Hebei, Zhejiang, and Guangdong, with Guangdong performing the worst at 0.23. Liaoning and Guangdong have shown modest improvements, whereas Hebei, Zhejiang, and Hainan declined, with Zhejiang experiencing the largest drop, from 0.65 in 2015 to 0.27 in 2020.

Government investment efficiency in the central region remains relatively low, indicating considerable room for improvement. Anhui and Jiangxi belong to the top tier, with average efficiencies above 0.9. Heilongjiang, Jilin, and Shanxi constitute the second tier, with scores ranging from 0.7 and 0.9. The remaining provinces fall below 0.7, with Henan performing the worst, averaging 0.43. Between 2015 and 2020, Heilongjiang (0.53 to 0.72), Anhui (0.93 to 1.00), and Hunan (0.62 to 0.90) showed notable improvement, with Hunan showing the largest increase. In contrast, Jilin, Henan, Shaanxi, and Hubei experienced declines, with Shanxi seeing the sharpest drop, from 1.00 to 0.37, which warrants close attention.

Table 7. Government investment efficiency

Cluster	DMU	Mean	2015	2016	2017	2018	2019	2020
Eastern	Beijing	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Tianjin	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Shanghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Liaoning	0.43	0.36	0.41	0.41	0.47	0.45	0.46
	Hebei	0.27	0.40	0.27	0.23	0.23	0.33	0.20
	Shandong	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Jiangsu	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Zhejiang	0.42	0.65	0.43	0.47	0.32	0.37	0.27
	Fujian	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Guangdong	0.23	0.19	0.29	0.18	0.22	0.19	0.31
	Hainan	0.99	1.00	1.00	1.00	1.00	1.00	0.92
	Average	0.76	0.78	0.76	0.75	0.75	0.76	0.74
Central	Heilongjiang	0.74	0.53	0.79	1.00	0.70	0.71	0.72
	Jilin	0.88	1.00	0.79	0.82	1.00	1.00	0.68
	Henan	0.43	0.45	0.38	0.67	0.41	0.35	0.32
	Shanxi	0.70	1.00	1.00	1.00	0.45	0.41	0.37
	Anhui	0.98	0.93	1.00	0.94	1.00	1.00	1.00
	Hubei	0.50	0.50	0.75	0.74	0.35	0.40	0.29
	Hunan	0.66	0.62	0.58	0.59	0.60	0.65	0.90
	Jiangxi	0.91	0.97	0.87	0.84	0.78	1.00	1.00
	Average	0.73	0.75	0.77	0.82	0.66	0.69	0.66
Western	Gansu	0.90	1.00	1.00	0.90	1.00	1.00	0.52
	Guizhou	0.89	1.00	1.00	0.66	0.85	0.83	1.00
	Ningxia	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Qinghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Shaanxi	0.37	0.36	0.43	0.42	0.36	0.32	0.34
	Yunnan	0.87	0.56	0.90	0.98	0.75	1.00	1.00
	Xinjiang	0.94	0.78	0.84	1.00	1.00	1.00	1.00
	Sichuan	0.23	0.22	0.30	0.24	0.21	0.25	0.17
	Chongqing	0.74	0.74	1.00	0.91	0.60	0.53	0.64
	Guangxi	0.98	0.86	1.00	1.00	1.00	1.00	1.00
	Inner Mongolia	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Average	0.81	0.77	0.86	0.83	0.80	0.81	0.79
Grand average		0.77	0.77	0.80	0.80	0.74	0.76	0.74

4.4. Poverty reduction (SDG 1) efficiency

Table 8 reports poverty reduction efficiency, with an average score of 0.87. Regionally, the eastern region leads at 0.92, followed by the western region at 0.87 and the central region at 0.79, reflecting slightly lower performance. Over time, efficiency rose from 2015 to 2017 but declined between 2017 and 2020.

Table 8. Poverty reduction efficiency

Cluster	DMU	Mean	2015	2016	2017	2018	2019	2020
Eastern	Beijing	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Tianjin	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Shanghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Liaoning	0.52	0.23	0.26	0.66	0.79	0.85	0.33
	Hebei	0.80	0.70	0.82	0.74	0.75	0.97	0.81
	Shandong	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Jiangsu	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Zhejiang	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Fujian	0.93	0.78	0.91	1.00	1.00	1.00	0.88
	Guangdong	0.98	0.92	1.00	1.00	0.99	1.00	1.00
	Hainan	0.87	0.82	0.92	0.77	1.00	0.91	0.83
	Average	0.92	0.86	0.90	0.92	0.96	0.97	0.90
Central	Heilongjiang	0.63	0.39	0.86	1.00	0.51	0.70	0.33
	Jilin	0.66	0.12	0.56	0.53	1.00	0.79	0.99
	Henan	0.71	0.65	0.76	0.88	0.80	0.78	0.38
	Shanxi	0.89	1.00	1.00	1.00	0.74	0.73	0.86
	Anhui	0.91	0.68	1.00	0.93	1.00	1.00	0.86
	Hubei	0.85	0.73	1.00	0.87	0.93	0.92	0.63
	Hunan	0.77	0.75	0.74	0.71	0.62	0.90	0.88
	Jiangxi	0.88	0.73	0.87	0.80	0.94	0.96	1.00
	Average	0.79	0.63	0.85	0.84	0.82	0.85	0.74
Western	Gansu	0.83	1.00	0.77	0.58	1.00	0.91	0.71
	Guizhou	0.99	1.00	1.00	0.98	0.98	0.98	1.00
	Ningxia	0.94	0.62	1.00	1.00	1.00	1.00	1.00
	Qinghai	0.91	1.00	1.00	1.00	0.84	0.84	0.77
	Shaanxi	0.70	0.44	0.70	0.89	0.88	0.90	0.38
	Yunnan	0.91	0.64	0.90	0.99	0.95	1.00	1.00
	Xinjiang	0.68	0.09	0.47	1.00	1.00	1.00	0.54
	Sichuan	0.80	0.55	0.76	0.89	0.86	0.86	0.88
	Chongqing	0.89	0.85	1.00	0.81	0.72	0.96	1.00
	Guangxi	0.95	0.75	0.98	1.00	1.00	1.00	1.00
	Inner Mongolia	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Average	0.87	0.72	0.87	0.92	0.93	0.95	0.84
Grand average		0.87	0.75	0.88	0.90	0.91	0.93	0.84

In the eastern region, Beijing, Tianjin, Shanghai, Shandong, Jiangsu, and Zhejiang achieved optimal efficiency. Guangdong and Fujian constitute the second tier, with scores ranging from 0.9 to 1.0. Hebei and Hainan are in the third tier, with values between 0.8 and 0.9. Liaoning is only 0.52. The coastal provinces in the eastern region have played a central role in poverty reduction.

In the western region, Inner Mongolia achieved the highest efficiency. Guizhou, Ningxia, Qinghai, and Guangxi also performed well, with scores between 0.9 and 1.0. Except for Xinjiang and Shaanxi, the remaining provinces-maintained efficiency above 0.8, reflecting substantial progress in poverty reduction.

In the central region, Anhui is the only province to exceed 0.9. Provinces such as Shanxi (0.89) and Jiangxi (0.88) also show strong performance and should leverage their strengths to guide neighboring provinces toward shared prosperity. In contrast, Heilongjiang (0.63), Jilin (0.66), and Henan (0.71) should adopt best practices to improve their poverty reduction efficiency.

4.5. Decent work and economic growth (SDG 8) efficiency

Table 9 reports the efficiency of decent work and economic growth, with an average efficiency of 0.93. Regionally, the eastern region leads at 0.97, followed by the western region at 0.92, and the central region at 0.88. Although efficiency experienced a notable decline in 2018, the overall trend has remained upward. China's strong economic growth, GDP performance, and sustained progress in stable, high-quality employment have supported the high efficiency observed in SDG 8.

In the eastern region, Beijing, Tianjin, Shanghai, Shandong, Jiangsu, and Zhejiang achieve the highest efficiency, while Liaoning recorded the lowest at 0.88. The remaining provinces scored between 0.9 to 1.0. This advantage reflects the region's advanced economic development, supported by a concentration of high-tech enterprises and abundant quality employment opportunities that attract talent and enhance performance. In the western region, Qinghai and Inner Mongolia also achieved optimal efficiency (1.00). Gansu, Ningxia, Shaanxi, Xinjiang, and Guangxi fall into the second tier with scores between 0.9 and 1.0. Guizhou, Yunnan, Sichuan, and Chongqing ranging from 0.8 to 0.9. In the central region, performance is generally lower, with only Shanxi (0.95) and Anhui (0.97) scoring above 0.9. The other six provinces recorded efficiencies between 0.8 and 0.9.

4.6. Comparison between SDG 1 and SDG 8

In Figure 4, a matrix is used to evaluate the performance of 30 provinces, with the average values serving as the threshold to divide the matrix into four quadrants. Fifteen provinces fall into the first quadrant. Among them, Beijing, Shanghai, Shandong, Jiangsu, Zhejiang, Tianjin, and Inner Mongolia achieved optimal scores of 1.00 for both SDG 1 and SDG 8, indicating outstanding performance in poverty reduction, employment, and economic development. Other provinces in the first quadrant include Guangdong, Ningxia, Guangxi, Qinghai, Anhui, Shanxi, and Hainan.

Table 9. Decent work and economic growth efficiency

Cluster	DMU	Mean	2015	2016	2017	2018	2019	2020
Eastern	Beijing	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Tianjin	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Shanghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Liaoning	0.88	0.87	0.87	0.92	0.83	0.95	0.85
	Hebei	0.91	0.94	0.86	0.96	0.89	0.98	0.81
	Shandong	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Jiangsu	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Zhejiang	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Fujian	0.96	1.00	0.95	1.00	0.88	0.98	0.97
	Guangdong	0.99	1.00	0.98	1.00	1.00	0.98	1.00
	Hainan	0.97	1.00	1.00	1.00	1.00	0.91	0.88
	Average	0.97	0.98	0.97	0.99	0.96	0.98	0.96
Central	Heilongjiang	0.86	0.82	1.00	1.00	0.72	0.81	0.78
	Jilin	0.84	0.86	0.66	0.80	1.00	1.00	0.72
	Henan	0.82	0.89	0.70	1.00	0.79	0.82	0.71
	Shanxi	0.95	1.00	1.00	1.00	0.86	0.93	0.89
	Anhui	0.97	0.87	1.00	0.94	1.00	1.00	1.00
	Hubei	0.89	0.88	1.00	0.89	0.80	0.99	0.81
	Hunan	0.89	0.77	0.79	0.96	0.83	1.00	1.00
	Jiangxi	0.85	0.77	0.73	0.79	0.87	0.94	1.00
	Average	0.88	0.86	0.86	0.92	0.86	0.94	0.86
Western	Gansu	0.92	1.00	1.00	0.77	1.00	1.00	0.72
	Guizhou	0.88	1.00	1.00	0.66	0.80	0.84	1.00
	Ningxia	0.99	0.94	1.00	1.00	1.00	1.00	1.00
	Qinghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Shaanxi	0.91	0.89	0.89	0.99	0.91	0.96	0.84
	Yunnan	0.83	0.56	0.77	0.96	0.69	1.00	1.00
	Xinjiang	0.97	0.94	0.87	1.00	1.00	1.00	1.00
	Sichuan	0.81	0.74	0.73	0.88	0.80	0.91	0.80
	Chongqing	0.89	0.77	1.00	0.87	0.80	0.92	0.97
	Guangxi	0.96	0.78	1.00	1.00	1.00	1.00	1.00
	Inner Mongolia	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Average	0.92	0.87	0.93	0.92	0.91	0.97	0.94
Grand average		0.93	0.91	0.92	0.95	0.91	0.96	0.92

Xinjiang, the only province in the second quadrant, performs poorly in SDG 1. As a key region in western China, it faces persistent poverty challenges due to a combination of geographic, economic, and social constraints. The province's vast area, dominated by deserts and mountains, suffers from fragile ecology and low agricultural productivity, limiting income sources. Its economy remains heavily reliant on resource extraction and agriculture,

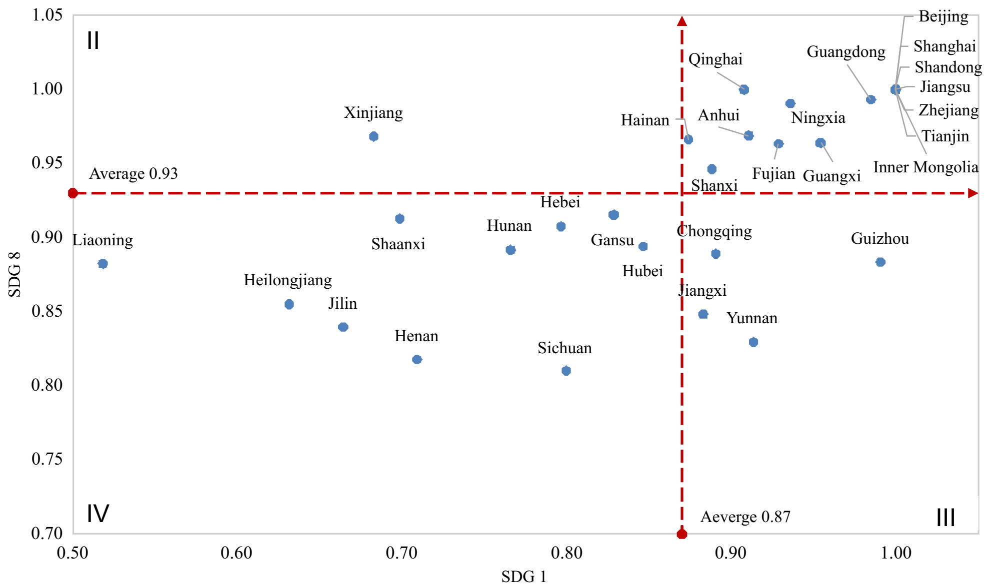

Figure 4. Comparison between SDG 1 and SDG 8

resulting in few non-agricultural job opportunities. Moreover, social and cultural barriers, including low education levels among some ethnic minorities, impede policy implementation and vocational training. Despite targeted government efforts, the risk of poverty recurrence remains significant.

The third quadrant comprises Guizhou, Chongqing, Yunnan, and Jiangxi, which demonstrate relatively strong performance in SDG 1 but fall below the average in SDG 8. The fourth quadrant comprises Hubei, Gansu, Hebei, Hunan, Sichuan, Shaanxi, Henan, Jilin, Heilongjiang, and Liaoning, all of which show poor performance in both SDG 1 and SDG 8.

4.7. Comparison of TGR

The TGR measures the distance between group frontier and meta frontier. A higher TGR indicates that the group frontier is technologically closer to the meta frontier. Figure 5 presents the overall TGR values for t30 provinces.

The eastern region reports the highest average TGR at 0.76, with five provinces attaining 1. Fujian and Hainan follow with TGR of 0.9, while Liaoning, Hebei, Zhejiang, and Guangdong exhibit relatively lower levels, indicating pronounced technological gaps. The western region posts an average TGR of 0.72, led by Inner Mongolia with score of 1. Ningxia, Qinghai, and Guangxi achieve values ranging from 0.9 to 1, while Shaanxi and Sichuan display substantial gaps, with TGRs of 0.27 and 0.17. The central region shows the widest gap, with an average TGR of only 0.57. With the exception of Anhui, which exceeds 0.9, the remaining provinces perform at or below the average level, with Henan recording the lowest TGR at 0.31.

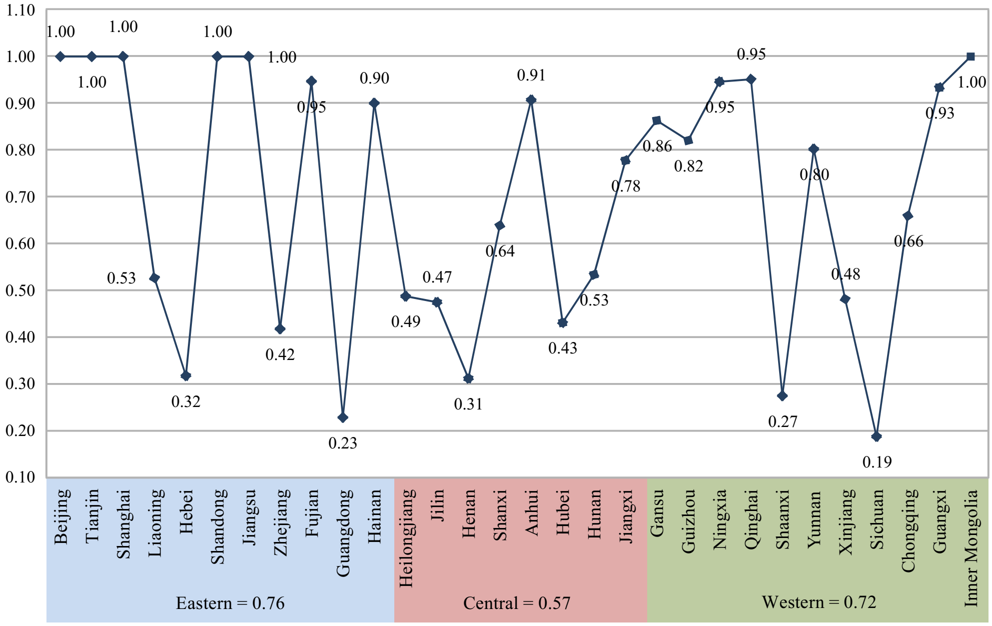

Figure 5. The TGR of 30 provinces

4.8. Kernel density analysis

To examine the temporal dynamics and distribution characteristics of efficiency, kernel density curves for overall efficiency are plotted in Figure 6.

Figure 6a shows the efficiency distribution of 30 provinces. The curve displays a bimodal pattern, with the main peak shifting rightwards, reflecting persistent polarization. The bandwidth initially narrows, then widens, while the rising peak height suggests a growing disparity, especially among high efficiency provinces.

Figure 6b shows the efficiency distribution of the eastern region, exhibiting a right-skewed bimodal pattern. From 2015 to 2020, the curve initially shifts rightward, then leftward, with the bandwidth narrowing before stabilizing. The peak reached its maximum in 2019 but declined sharply afterward, indicating a reduced efficiency gap and a deceleration of polarization.

Figure 6c illustrates the central region's transition from a bimodal to a multimodal distribution, featuring a right-skewed main peak. The curve shows directional fluctuations, with widening bandwidth and declining peak height, suggesting increasing inter-provincial disparities and a more fragmented efficiency structure.

Figure 6d depicts the western region's transition from a bimodal to a multimodal pattern. The main peak shifts rightward, the curve narrows, and peak height rises until 2019 before declining, yet remaining above 2015 levels. This trend indicates growing polarization among high-efficiency provinces, although with emerging signs of stabilization.

Figure 7a depicts the distribution of government investment efficiency. The curve displays a bimodal pattern with a rightward-shifted main peak, reflecting pronounced polarization, particularly among high-efficiency provinces. Between 2015 and 2017, the main peak rises while the bandwidth narrows, indicating intensified polarization and reduced inter-provincial disparities. After 2017, the peak declines with fluctuations, and polarization begins to moderate.

Figure 7b shows the SDG 1 efficiency distribution, exhibiting a multimodal pattern with a right-skewed main peak, indicating persistent multipolar differentiation. From 2015 to 2019, the main peak rises sharply while the bandwidth narrows, reflecting intensified polarization and reduced inter-provincial gaps. By 2020, the peak declines, the bandwidth expands, and inter-provincial disparities increase. Overall, although efficiency improved, polarization intensified relative to 2015.

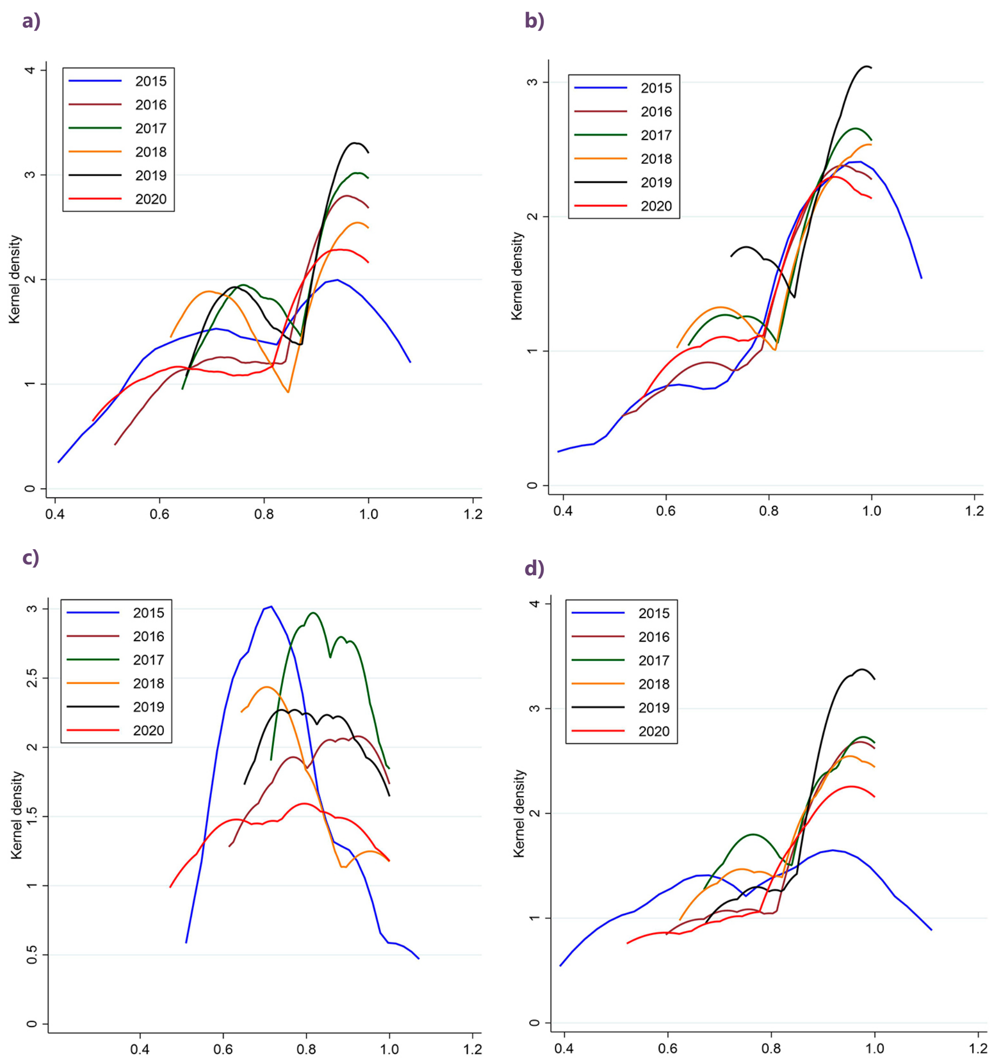

Figure 6. Kernel density distribution for overall efficiency

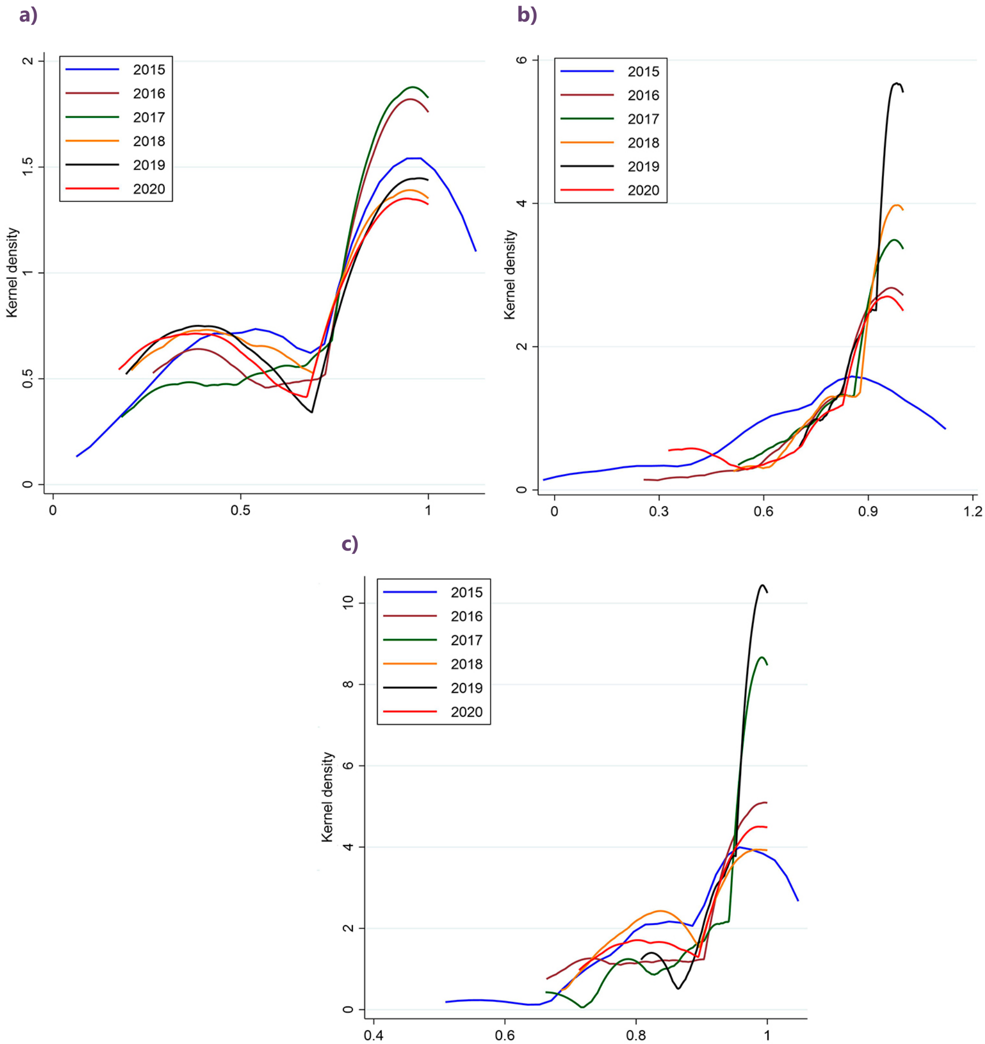

Figure 7. Kernel density distribution of government investment, SDG 1, and SDG 8

Figure 7c depicts SDG 8 efficiency, exhibiting a pattern similar to that of SDG 1. The curve shows multiple peaks with a rightward shifted main peak. From 2015 to 2020, the main peak fluctuates before eventually rising. The bandwidth first narrows, then expands, and narrows again. This suggests a reduced efficiency gap, especially in the western region, accompanied by a moderate increase in polarization.

5. Discussion

This paper integrates poverty reduction, employment, and economic growth into a unified analytical framework, providing a systematic assessment of SDG 1 and SDG 8 performance in China. Based on the core components of both goals, input and output variables are selected across economic, social, and environmental dimensions to construct a meta parallel two-stage dynamic RDM-DDF model. This model allows joint evaluation of SDG 1 and SDG 8 within a parallel system, facilitating a clearer understanding of their synergistic interactions. Moreover, the RDM approach effectively handles negative values in the dataset, overcoming infeasibility issues commonly encountered in traditional efficiency evaluations.

The overall efficiency is moderate, with SDG 8 outperforming SDG 1. A pronounced regional imbalance exists among the eastern, central, and western regions, reflecting China's current economic landscape. The higher efficiency of SDG 8 reflects China's rapid economic growth over the past two decades. In contrast, the relatively low efficiency of SDG 1 largely results from persistent relative poverty and widening income inequality. To enhance SDG 1 performance, future efforts should focus on narrowing the urban-rural income gap and mitigating the risk of poverty relapse.

Several limitations exist. First, the assessment sustainable economic development involves multiple dimensions, including technological innovation, environmental protection, and cultural advancement (Ahmad et al., 2023). However, not all factors were incorporated into the indicator system or research framework. Although this omission does not compromise the validity of the efficiency results or core conclusions, it limits the comprehensiveness of the analysis. Second, poverty reduction is measured using indicators of absolute poverty, including the proportion of the population not living in poverty and the base level of the minimum living allowance. These metrics primarily capture the conditions of the most disadvantaged groups, whereas relative poverty, as reflected in income inequality and regional disparities, remains a significant challenge (Wan et al., 2021; Zou et al., 2023). Future research should address these gaps by expanding the evaluation framework for sustainable development and incorporating a more detailed analysis of relative poverty and common prosperity.

6. Conclusions and suggestions

This study applies a meta parallel two-stage dynamic RDM-DDF model and kernel density estimation to assess SDG 1 and SDG 8 efficiency across 30 Chinese provinces. Keys findings are as follows:

First, overall efficiency averages 0.67, with the eastern region (0.72) outperforming the west (0.70) and central region (0.57). Eastern provinces, including Beijing, Shanghai, and Jiangsu, show strong leadership, while western provinces such as Yunnan, Xinjiang, and Guangxi achieve notable gains. The central region lags behind.

Second, government investment efficiency averages 0.77, highest in the west (0.81) and lowest in the central region (0.73). Shaanxi (0.37) and Sichuan (0.23) underperform in the west, while six eastern provinces reach full efficiency (1.00).

Third, SDG 8 efficiency (0.93) exceeds SDG 1 (0.87). In SDG 1, eastern and most western provinces perform well, whereas the central region lags, with Anhui, Shanxi, and Jiangxi faring relatively better. In SDG 8, all provinces score above 0.8, led by the east (0.97), then the west (0.92) and central region (0.88).

Fourth, the eastern region shows the highest TGR (0.76), followed by the west (0.72) and central region (0.57). By 2020, the west surpasses the east in TGR, while the central region remains behind.

Fifth, kernel density results reveal rising polarization: disparities decrease between eastern and western provinces but widen in the central region. High-efficiency provinces show more pronounced polarization in government investment, with SDG 1 and SDG 8 displaying similar patterns.

According to the main findings above, the following suggestions are provided:

First, to reduce regional disparities and improve stage-specific efficiencies, provinces should define functional roles and promote coordinated spatial development. Leading provinces like Beijing, Jiangsu, and Ningxia should enhance agglomeration effects and drive broader regional spillovers in SDG progress.

Second, significant regional technology gaps require differentiated strategies. The central region should enhance openness, promote technology diffusion, and strengthen its economic base. The eastern region should optimize resource allocation, while the western region should focus on applying existing technologies and boosting investment in green energy.

Third, government investment continues to drive SDGs, but inefficiencies persist, particularly in eastern and central provinces. Resource allocation should prioritize connectivity, prevent redundancy, and adopt a green, intensive development approach. A balanced mix of government planning and market mechanisms is needed to enhance investment outcomes.

Fourth, although absolute poverty has been eliminated, relative poverty persists, particularly among vulnerable groups. Promoting SDG 8 through employment-friendly policies, vocational training, and targeted industrial development is essential to break the poverty cycle through economic growth.

Funding

This paper was supported by a grant from the Major Programs of the National Social Science Foundation of China (22&ZD180); Postgraduate Research & Practice Innovation Program of Jiangsu Province (KYCX25_1828).

References

Adams, R. H. (2004). Economic growth, inequality and poverty: Estimating the growth elasticity of poverty. *World Development*, *32*(12), 1989–2014. https://doi.org/10.1016/j.worlddev.2004.08.006

Aghion, P., & Bolton, P. (1997). A theory of trickle-down growth and development. *The Review of Economic Studies*, *64*(2), 151–172. https://doi.org/10.2307/2971707

Ahmad, N., Youjin, L., Žiković, S., & Belyaeva, Z. (2023). The effects of technological innovation on sustainable development and environmental degradation: Evidence from China. *Technology in Society*, *72*, Article 102184. https://doi.org/10.1016/j.techsoc.2022.102184

AlBataineh, A. (2024). The effect of remittances on poverty and economic growth in Jordan: Evidence from augmented autoregressive distributed lag model. *Technological and Economic Development of Economy*, *30*(6), 1709–1731. https://doi.org/10.3846/tede.2024.21845

Bourguignon, F. (2003). The growth elasticity of poverty reduction: Explaining heterogeneity across countries and time periods. In T. S. Eicher & S. J. Turnovsky (Eds.), *Inequality and growth*: *Theory and policy implications* (pp. 1–26). MIT Press. https://doi.org/10.7551/mitpress/3750.003.0004

Caminada, K., & Goudswaard, K. (2009). Effectiveness of poverty reduction in the EU: A descriptive analysis. *Poverty & Public Policy*, *1*(2), 1–49. https://doi.org/10.2202/1944-2858.1023

Chung, Y. H., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. *Journal of Environmental Management*, *51*(3), 229–240. https://doi.org/10.1006/jema.1997.0146

Duan, C., Zhou, Y., Cai, Y., Gong, W., Zhao, C., & Ai, J. (2022). Investigate the impact of human capital, economic freedom and governance performance on the economic growth of the BRICS. *Journal of Enterprise Information Management*, *35*(4–5), 1323–1347. https://doi.org/10.1108/JEIM-04-2021-0179

Färe, R., & Grosskopf, S. (2000). Theory and application of directional distance functions. *Journal of Productivity Analysis*, *13*, 93–103. https://doi.org/10.1023/A:1007844628920

Färe, R., Grosskopf, S., & Whittaker, G. (2007). Network DEA. In J. Zhu & W. D. Cook (Eds.), *Modeling data irregularities and structural complexities in data envelopment analysis* (pp. 209–240). Springer. https://doi.org/10.1007/978-0-387-71607-7_12

Färe, R., & Grosskopf, S. (2010). Directional distance functions and slacks-based measures of efficiency. *European Journal of Operational Research*, *200*(1), 320–322. https://doi.org/10.1016/j.ejor.2009.01.031

Friedberg, R. M., & Hunt, J. (2018). The impact of immigrants on host country wages, employment and growth. In M. M. Suárez-Orozco, C. Suárez-Orozco, & D. Qin-Hilliard (Eds.), *The new immigrant in the American economy* (pp. 89–110). Routledge. https://doi.org/10.4324/9781315054193-4

Hangoma, P., & Surgey, G. (2019). Contradictions within the SDGs: Are sin taxes for health improvement at odds with employment and economic growth in Zambia. *Globalization and Health*, *15*, Article 82. https://doi.org/10.1186/s12992-019-0510-x

Hogendoorn, B., Leopold, T., & Bol, T. (2020). Divorce and diverging poverty rates: A risk-and-vulnerability approach. *Journal of Marriage and Family*, *82*(3), 1089–1109. https://doi.org/10.1111/jomf.12629

Kao, C. (2009). Efficiency decomposition in network data envelopment analysis: A relational model. *European Journal of Operational Research*, *192*(3), 949–962. https://doi.org/10.1016/j.ejor.2007.10.008

Kapsos, S. (2004). *Estimating growth requirements for reducing working poverty*: *Can the world halve working poverty by 2015?* (Employment Strategy Papers). International Labour Office.

Kerr, W. C., Kaplan, M. S., Huguet, N., Caetano, R., Giesbrecht, N., & McFarland, B. H. (2017). Economic recession, alcohol, and suicide rates: Comparative effects of poverty, foreclosure, and job loss. *American Journal of Preventive Medicine*, *52*(4), 469–475. https://doi.org/10.1016/j.amepre.2016.09.021

Kroft, K., & Notowidigdo, M. J. (2016). Should unemployment insurance vary with the unemployment rate? Theory and evidence. *The Review of Economic Studies*, *83*(3), 1092–1124. https://doi.org/10.1093/restud/rdw009

Kuznets, S. (2019). Economic growth and income inequality. In M. A. Seligson (Ed.). *The gap between rich and poor* (pp. 25–37). Routledge. https://doi.org/10.4324/9780429311208-4

Menton, M., Larrea, C., Latorre, S., Martinez-Alier, J., Peck, M., Temper, L., & Walter, M. (2020). Environmental justice and the SDGs: From synergies to gaps and contradictions. *Sustainability Science*, *15*, 1621–1636. https://doi.org/10.1007/s11625-020-00789-8

O'Donnell, C. J., Rao, D. P., & Battese, G. E. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics*, *34*, 231–255. https://doi.org/10.1007/s00181-007-0119-4

Portela, M. S., Thanassoulis, E., & Simpson, G. (2004). Negative data in DEA: A directional distance approach applied to bank branches. *Journal of the Operational Research Society*, *55*(10), 1111–1121. https://doi.org/10.1057/palgrave.jors.2601768

Ravallion, M. (1995). Growth and poverty: Evidence for developing countries in the 1980s. *Economics Letters*, *48*(3–4), 411–417. https://doi.org/10.1016/0165-1765(94)00620-H

Ravallion, M. (2001). Growth, inequality and poverty: Looking beyond averages. *World Development*, *29*(11), 1803–1815. https://doi.org/10.1016/S0305-750X(01)00072-9

Sen, A. (2020). The possibility of social choice. In S. Sarasvathy, N. Dew, & S. Venkataraman (Eds.), *Shaping entrepreneurship research* (pp. 298–339). Routledge. https://doi.org/10.4324/9781315161921-15

Shahbaz, M., Song, M., Ahmad, S., & Vo, X. V. (2022). Does economic growth stimulate energy consumption? The role of human capital and R&D expenditures in China. *Energy Economics*, *105*, Article 105662. https://doi.org/10.1016/j.eneco.2021.105662

Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, *27*(3), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

The State Council Information Office of the People's Republic of China. (2021). *White Paper on Chinese Practice of human poverty reduction* (China's Practice in Poverty Alleviation, April 6, 2021). https://www.gov.cn/zhengce/2021-04/06/content_5597952.htm

Tone, K., & Tsutsui, M. (2014). Dynamic DEA with network structure: A slacks-based measure approach. *Omega*, *42*(1), 124–131. https://doi.org/10.1016/j.omega.2013.04.002

Wan, G., Hu, X., & Liu, W. (2021). China's poverty reduction miracle and relative poverty: Focusing on the roles of growth and inequality. *China Economic Review*, *68*, Article 101643. https://doi.org/10.1016/j.chieco.2021.101643

Wang, H., Li, S., & Zhang, H. (2024). Nexus between country governance, globalization, sustainable development policy, fair trade and economic sustainability: A mediation-moderation approach. *Technological and Economic Development of Economy*, *30*(5), 1435–1456. https://doi.org/10.3846/tede.2024.21751

Zhang, Y., Zhou, X., & Lei, W. (2017). Social capital and its contingent value in poverty reduction: Evidence from Western China. *World Development*, *93*, 350–361. https://doi.org/10.1016/j.worlddev.2016.12.034

Zhang, J., Wang, S., Pradhan, P., Zhao, W., & Fu, B. (2022). Untangling the interactions among the Sustainable Development Goals in China. *Science Bulletin*, *67*(9), 977–984. https://doi.org/10.1016/j.scib.2022.01.006

Zhou, Y., Li, Y., & Liu, Y. (2020). The nexus between regional eco-environmental degradation and rural impoverishment in China. *Habitat International*, *96*, Article 102086. https://doi.org/10.1016/j.habitatint.2019.102086

Zou, W., Cheng, X., Fan, Z., & Lin, C. (2023). Measuring and decomposing relative poverty in China. *Land*, *12*(2), Article 316. https://doi.org/10.3390/land12020316