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# Commercial banks performance, ownership types and operations efficiency decomposition in China: a comparative analysis

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This study aims to investigate the operations efficiency and decomposition of the banking sector in the Chinese mainland and conduct a comparative analysis on domestic and foreign commercial banks with different ownership types. In view of the development capability, liquidity, safety, and profitability of banks, the operations process of banks is first subdivided into a two-stage network structure, namely capital flow and capital profitability stage. Then, the non-performing loans are used as a carry-over variable connecting two adjacent periods in the first stage, to establish a novel two-stage dynamic network structure. The dynamic data envelopment analysis with network structure methodology is used to decompose the efficiency of the operations into two constituent components to give internal explanations for the root causes of inefficiency. Results show that foreign-funded banks performed better than Chinese-funded banks on average during 2016–2020, and there exists a significant divergence among different ownership types, which reflects the significant differences in their operating levels. Besides, private banks performed best among the five types of domestic banks, and rural banks performed the worst. Finally, capital flow efficiency is significantly better than capital profitability efficiency, and the main internal cause of low efficiency in the banking sector is the inadequacy of capital profitability. The new insights reveal that banks operating in China should manage their capital profitability effectively to enhance overall operations performance.

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## Introduction

According to the statistical data released by the National Bureau of Statistics of China, during the 13th Five-Year Plan (2016–2020) period, China's GDP growth rate has been continuously declining, decreasing from 6.85% in 2016 to 2.24% in 2020. However, the economic slowdown has not affected the dominant position of the banking system in China's financial system, and banks continue to play a crucial role in achieving stable and healthy development of both the real and virtual economies and promoting sustainable growth of the national economy (Cerutti et al. 2023; Chen et al. 2023; Jing et al. 2024). Data published by the China Banking and Insurance Regulatory Commission at the end of 2020 shows that the capital scale of China's banking industry has maintained rapid growth, with total capital reaching 319.7 trillion CNY at the end of 2020, a year-on-year increase of 10.1%. Additionally, the capital quality of the banking industry has improved, with the overall non-performing loan ratio remaining stable at 1.84%, a decrease of 0.02% compared to the previous year. Currently, the world is in a situation of unprecedented change, especially the persistent global inflation, and increasing economic downward pressure in China, which have significantly increased uncertainties in both domestic and international environments, leading to a slowdown in the profitability growth of the banking industry (Liang et al. 2023; Lu et al. 2024).

The 14th Five-Year Plan (2021–2025) is a key period for China's banking industry to accelerate its transformation and upgrade to effectively support the new development pattern of the national economy through its high-quality and sustainable development. During this stage, China's real economy will have an urgent need for high-quality financial services, and the future development of the banking industry will require stronger endogenous drivers. In the current era and economic context, commercial banks, which aim to serve the real economy, face the core objective of achieving sustainable and healthy growth under the constraints of tightening capital and increasing risks. To achieve this goal, the essence is to effectively enhance the core competitiveness of commercial banks. Operations efficiency is a concentrated manifestation of competitiveness (Li et al. 2023; Takahashi and Vasconcelos, 2024). Therefore, it is reasonable and effective to measure the operations efficiency of commercial banks in China during the 13th Five-Year Plan period, systematically summarize and analyze historical development experiences, and help banking managers further understand their operating levels, thereby effectively formulating strategies to enhance future operating levels and core competitiveness. At the same time, this can also provide theoretical references for banking regulators to formulate relevant regulatory policies.

A systematic summary of existing literature reveals that the research methods used to assess the operations efficiency of commercial banks mainly include parametric approaches like stochastic frontier analysis (SFA) or non-parametric approaches like data envelopment analysis (DEA). According to Emrouznejad and Yang (2018), the DEA method based on non-parametric mathematical programming is a very mature and widely used efficiency measurement method in various fields. The advantage of the DEA method is that it does not require a predetermined form of the production function, and the calculation results can reflect the path to improve the efficiency of Decision-Making Units (DMUs), thereby attracting extensive attention from scholars (Zhu et al. 2021a, 2021b, 2024; Zhu and Zhu, 2023). Therefore, this paper intends to use the DEA method to measure the operations efficiency of commercial banks. Based on the operations structure of the banking system, research on the operations efficiency measurement of commercial banks using the DEA method can be summarized from single-stage and multi-

stage perspectives. The single-stage DEA method considers commercial banks as a "black box", ignoring the internal processes of its operation and focusing only on initial input indicators and final output indicators. In the early days of the DEA method's inception, almost all studies were based on this perspective. Later, as the DEA method continued to develop, multi-stage DEA methods emerged, which further divided the operations process of commercial banks into several subsystems, aiming to open the "black box" of commercial bank operations.

Sherman and Gold (1985) first used the DEA method to study the efficiency of branch offices of 14 American banks, and since then, the DEA method has gradually become one of the important methods for measuring the efficiency of commercial banks. The research in the early period mainly applies the DEA method to comparative studies between different commercial banks, or between different commercial banks in different countries. This method is also applicable to comparative efficiency studies between different subsidiary branches of the same bank. Omrani et al. (2023) proposed a robust DEA approach for discrete scenarios to measure the efficiency of bank branches. In addition, some scholars have attempted to use the DEA method to compare and analyze the operations efficiency of commercial banks with different properties. Ariff and Luc (2008) combined the DEA method with Tobit regression to measure the cost efficiency and profit efficiency of Chinese listed commercial banks. Wanke et al. (2016) applied the DEA approach to assess the performance of 128 OECD banks. Later, Wanke et al. (2023) developed a new DEA-Ratio model to assess the efficiency of 124 OECD banks over a twelve-year time window. Zhu et al. (2021a) applied the classic DEA model to calculate the operations efficiency of private, public, and foreign banks in Pakistan from 2006 to 2017 and conducted a comparative analysis. Shi et al. (2023) utilized slacks-based DEA to evaluate the performance of commercial banks in China, and Antunes et al. (2024) employed the DEA approach to measure the cost efficiency of the banking sector in China.

The above-mentioned single-stage DEA method does not consider the intermediate products (also known as intermediate variable) between the initial input and final output of commercial banks, so the efficiency measurement results cannot reflect the internal reasons for the operations inefficiency of the banking sector. Therefore, based on the internal operations structure of commercial banks, many scholars have begun to use multi-stage DEA methods to study the overall operations efficiency and stage operations efficiency of commercial banks. Ebrahimnejad et al. (2014) constructed a three-stage DEA model consisting of two independent parallel stages, with the output of the second stage serving as the input for the third stage. Zha et al. (2016) divided the operations process of banks into production and profitability stages and studied the efficiency of each stage. Zhou et al. (2018) divided the commercial operation process into capital organization, capital allocation, and profitability stages, and studied the efficiency of each stage of listed commercial banks in China from 2014 to 2016. Liu et al. (2020, 2021) also divided the network structure of the operations process of commercial banks into two stages series or parallel systems. Wu et al. (2023) used a two-stage network DEA to measure the overall efficiency of commercial banks in China with a data set of 27 samples from 2006 to 2020. Wang et al. (2024) introduced a three-stage DEA-Tobit approach to assess the operations efficiency of Chinese-listed commercial banks.

Although the network DEA method has opened the "black box" of commercial bank operations, considering the complexity and continuous impact of banking activities, i.e., the current operating conditions may have a lagging impact on later periods, the measurement results obtained by ignoring the connections between the production and operation activities of commercial banks in different periods may be biased. Therefore, some

scholars have begun to study dynamic DEA models with network structures to address this problem (Kao and Liu, 2014; Chen et al. 2018; Zhou et al. 2019). The dynamic network DEA model considers both the intermediate variables (i.e., linkage variables) of commercial bank operations and the lagging impact of carry-over variables (i.e., carry-over variable) on subsequent periods of operation, making the efficiency assessment results more reasonable. Mariz et al. (2018) found through a review of DEA-related literature published from 1996 to 2016 that the dynamic network DEA model is a very promising new field worthy of in-depth research and a hot research direction for the future development of DEA models. Dynamic network DEA models can be classified into non-radial and radial types, with the non-radial dynamic network DEA model mainly based on the dynamic network SBM-DEA model proposed by Tone et al. (2014, 2019). Qian et al. (2018) applied a dynamic network DEA model to analyze the operations efficiency of Islamic banks. Yu et al. (2021) used a dynamic network DEA model based on SBM to measure the operations efficiency of 22 commercial banks in Taiwan, China, from 2008 to 2016. Kweh et al. (2024) applied dynamic network DEA to assess resources management and profitability efficiencies using 287 US commercial banks in 2010–2020 as an example, and Huang et al. (2024) used dynamic network DEA framework to investigate operations efficiency of credit business in Chinese commercial banks in 2016–2022. Radial dynamic network DEA models are mainly based on the dynamic network DDF-DEA model proposed by Fukuyama and Weber (2017a) and Fukuyama and Weber (2017b). Compared to non-radial dynamic network SBM-DEA models, radial models may overestimate efficiency due to their inability to consider the impact of slack, making them less commonly applied.

In outline, many scholars have conducted comparative research on the overall operations efficiency and its decomposition of commercial banks using various complex and diverse dynamic network DEA models from different perspectives. However, considering the difficulty of comparing the relative importance of different operation stages and periods of commercial banks, there is currently no commonly recognized method for determining period weights and stage weights in the existing literature. Previous studies typically treat the stage weights and period weights as equal or draw on the exponential decay model<sup>2</sup> from the field of physics to calculate period weights. Obviously, these two methods may result in biased stage weights and period weights, and the assessment results of overall efficiency may not correspond to the actual situations. Therefore, this paper does not directly use the dynamic network DEA model to measure the overall operations efficiency of commercial banks, but first extends the existing single-stage DEA model to calculate overall operations efficiency, and then introduces the dynamic network DEA model to decompose the internal operations efficiency of commercial banks, thereby indirectly identifying the internal reasons for the operations inefficiency of commercial banks. Based on the above discussions, the main contributions of this paper are as follows:

- (1) This work contributes to the existing literature by assessing and decomposing operations efficiency among six types of domestic and foreign-funded commercial banks with different ownership in the Chinese mainland using the DEA model. By conducting a comparative analysis, research results can be adopted as a guidance document that helps to reconcile the proven issues in Chinese banking sector practices and serve bankers and policymakers to achieve competitive and sustainable goals. Here, 127 commercial banks are selected from domestic banks that include national-owned commercial banks, stock commercial banks, urban commercial banks, rural commercial banks, private commercial banks, and 13 foreign-funded commercial banks operating in China mainland. By reviewing the existing literature, there is no such comparative study on the above six ownership types of domestic and foreign-funded commercial banks in the Chinese mainland at the same time or selects so many commercial bank samples, to carry out a general analysis of operations efficiency and its decomposition. This study may devote cumulative efforts to the assessment of operations efficiency and its decomposition in the banking sector.
- (2) This work develops a novel, complex, dynamic network structure for the internal operations process of banks. Specifically, the internal operations process of banks is subdivided into a two-stage network structure, namely capital flow and capital profitability stage, with non-performing loans used as a carry-over variable connecting the first stage of two adjacent periods, to give the internal explanations for the root causes of inefficiency. Compared with the relevant literature, this new two-stage network structure has some nice features. For instance, it combines the deposit attraction and liability allocation stages of commercial banks into one capital flow stage, to avoid the problem of repeated use of inputs at different stages. Additionally, this study does not share inputs from the first stage in the second or third stage, to address the issue that the actual utilization rate of the first stage's inputs in the subsequent stages is hard to ascertain, and directly treating them as fully utilized could lead to biased measurement results. Finally, the new network structure considers the lagged impact of previous non-performing loans in the capital flow stage and includes current non-performing loans as an undesirable output in the capital profitability stage, which makes the measurement results more reasonable.

The rest section of this paper is designed as below. Section “Efficiency measurement model” introduces the efficiency measurement model, i.e. super-efficiency slacks-based measure DEA and dynamic network slacks-based DEA model. Section “Assessment and analysis of overall operations efficiency” measures and analyzes the overall operations efficiency in the Chinese banking sector in 2016–2020. A new dynamic two-stage network structure and decomposition of operations efficiency for commercial banks are presented in the section “Operations efficiency decomposition and analysis”. According to the findings, conclusions, limitations and some managerial implications to enhance the operations efficiency of China's banking sector are provided in the section “Conclusions and managerial implications”.

### Efficiency measurement model

**Super slacks-based measure DEA model with undesirable-outputs.** Since 1978, the DEA method has been developed by many scholars, and its application fields have also extended rapidly. Various DEA models have been continuously developed and applied in the evaluation of public organizations such as education, healthcare, and government, as well as private organizations such as banks, insurance companies, and service providers (Farah and Amara, 2023; Zhu et al. 2021a, 2021b, 2024; Zhu and Zhu, 2023). However, both the classical DEA-CCR model and the DEA-BCC model have their shortcomings. For example, when the number of decision-making units is small, but the input–output quantity is large, it is common to have multiple DMU efficiency values of 1, which will not effectively distinguish the relative efficiency of these effective DMUs (Tone, 2020; Zhu and Zhu, 2023). In addition, traditional DEA models rely on a fundamental assumption that inputs must be reduced as much as possible and outputs must be expanded as much as possible (Tone and Tsutsui, 2014; Zhu and Zhu, 2023; Zhu et al. 2024). However, this is often not the case in real production activities. Some production processes may produce obvious by-products, many of which are products that

people do not expect to produce, which are called unexpected or undesirable outputs. For example, the industry activities gain the industry goods through investing capital, labor, resources, energy, etc., but it is often accompanied by undesirable outputs like environmental pollutants (Zhu and Zhu, 2023). Moreover, the banking systems obtain profits like interest income, non-interest income, etc., through investing capital, labor, and other resource, but the operations process would also cause undesirable outputs like non-performing loans (Zhu et al. 2024).

In view of the above issues, Zhu and Zhu (2023) constructed a super slacks-based measure DEA approach with undesirable outputs, by removing the  $DMU_j$  to be assessed from the reference set, namely a new constraint  $j \neq 0$  has been added to the model proposed by Tone (2003), and constructing a new reference set according to the rest of DMUs to obtain the total ranking for all DMUs, the specific expression is as below:

$$\min \theta_0 = \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2} \left( \sum_{r=1}^{s_1} \frac{s_r^{g+}}{y_{r0}^g} + \sum_{r=1}^{s_2} \frac{s_r^{b-}}{y_{r0}^b} \right)}$$

$$s.t. \begin{cases} \sum_{j=1}^n \lambda_j x_{ij} + s^- = \theta_0 x_{i0} & j \neq 0 \\ \sum_{j=1}^n \lambda_j y_{rj} + s^{b-} = \theta_0 y_{r0}^b, r = 1, 2, \dots, s_1 & j \neq 0 \\ \sum_{j=1}^n \lambda_j y_{rj} - s^{g+} = \theta_0 y_{r0}^g, r = 1, 2, \dots, s_2 & j \neq 0 \\ \lambda_j \geq 0, s^- \geq 0, s^{g+} \geq 0, s^{b-} \geq 0 \end{cases} \quad (1)$$

Here the objective function  $\theta_0$  is super-efficiency score of  $DMU_0$ .  $x_0$ ,  $y_0^b$ , and  $y_0^g$  represent input variables, undesirable outputs, and desirable outputs of  $DMU_0$ , respectively. Moreover,  $s^-$ ,  $s^{b-}$  and

$s^{g+}$  are the slacks of the above variables, and  $m$ ,  $s_1$ ,  $s_2$  stands for the number of above variables, respectively. Where we have  $s_1 + s_2 = s$ .

The equivalent linear programming of expression (1) is as follows:

$$\theta_0^* = \min \varphi + \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{i0}}$$

$$s.t. \begin{cases} 1 = \varphi - \frac{1}{s_1 + s_2} \left( \sum_{r=1}^{s_1} \frac{s_r^{g+}}{y_{r0}^g} + \sum_{r=1}^{s_2} \frac{s_r^{b-}}{y_{r0}^b} \right) \\ \varphi x_0 - \sum_{j=1}^n \lambda_j x_j + S^- \geq 0 & j \neq 0 \\ \varphi y_0^b - \sum_{j=1}^n \lambda_j y_j^b + S^{b-} \geq 0 & j \neq 0 \\ \sum_{j=1}^n \lambda_j y_j^g - \varphi y_0^g + S^{g+} \geq 0 & j \neq 0 \\ \lambda, S^-, S^{b-}, S^{g+} \geq 0 \end{cases} \quad (2)$$

Let an optimal solution of linear programming (2) be  $\theta_0^*$ ,  $\Lambda^*$ ,  $S^{*-}$ ,  $S^{g*+}$ ,  $S^{b*-}$ . Then the optimal solution of expression (1) can be expressed by  $\theta_0 = \theta_0^*$ ,  $\lambda^* = \Lambda^*/\varphi^*$ ,  $s^{*-} = S^{*-}/\varphi^*$ ,  $s^{g*+} = S^{g*+}/\varphi^*$ ,  $s^{b*-} = S^{b*-}/\varphi^*$ . For more details, please see Zhu and Zhu (2023).

**Dynamic network slacks-based DEA with undesirable outputs.** The non-radial dynamic network DEA model proposed by Tone and Tsutsui (2014) is currently the mainstream method for efficiency evaluation in the banking industry and other fields and has been used and expanded by many scholars. The relevant symbols and definitions in the modeling process are shown in Table 1.

**Table 1 Abbreviations and descriptions.**

Abbreviations	Descriptions
$DMU_j$	The $j$ th $DMU$ , $j = 1, 2, \dots, n$ , i.e. the total number of $DMU_s$ is $n$ .
$k$	$k$ node, $k = 1, 2, \dots, K$ , that is, the number of nodes is $K$ , and each node represents a sub-stage.
$t$	The $t$ period, $t = 1, 2, \dots, T$ , that is, there are $T$ periods in the observation period.
$m_k, r_k$	Node $k$ has $m_k$ input variables and $r_k$ output variables.
$x_{mjk}^t$	$DMU_j$ is the $m$ th input variable in the epoch $t$ , node $k$ , $m = 1, 2, \dots, m_k$ , $x_{mjk}^t \in R_+$ .
$y_{rjk}^t$	$DMU_j$ is the $m$ th input variable in the epoch $t$ , node $k$ , $r = 1, 2, \dots, r_k$ , $y_{rjk}^t \in R_+$ .
$\lambda_k^t, \lambda_{jk}^t$	In the period $t$ , the weight coefficient of node $k$ , $\lambda_k^t \in R_+$ ; $\lambda_{jk}^t$ is a vector form of $\lambda_{jk}^t$ .
$z_{j(kh)}^t$	The $l$ th connection variable (also known as the intermediate product, i.e., the Linkage variable) between the node $k$ and the node $h$ of $DMU_j$ is $l = 1, 2, \dots, L_{khr}$ , that is, the number of connection variables is $L_{khr}$ , and $z_{j(kh)}^t \in R_+$ .
$z_{jk}^{(t,t+1)}$	At node $k$ , the $l$ th junction transition between period $t$ and period $t + 1$ (i.e., the carry-over variable), $l = 1, 2, \dots, L_k$ , that is, the number of junction transitions is $L_k$ , and $z_{jk}^{(t,t+1)} \in R_+$ .
$\mathbf{x}_{ok}^t, \mathbf{y}_{ok}^t$	The input and output vectors of $DMU_0$ in the period $t$ and node $k$ are respectively deputedized.
$\mathbf{z}_{j(kh)}^t, \mathbf{z}_{jk}^{(t,t+1)}$	Vector forms of connection and transition variables, respectively, with the subscript letters meaning the same as above.
$\mathbf{X}_k^t, \mathbf{Y}_k^t$	$\mathbf{X}_k^t = (\mathbf{x}_{1k}^t, \mathbf{x}_{2k}^t, \dots, \mathbf{x}_{nk}^t) \in R_n^m$ , $\mathbf{Y}_k^t = (\mathbf{y}_{1k}^t, \mathbf{y}_{2k}^t, \dots, \mathbf{y}_{rk}^t) \in R_n^r$ , the input and output matrices of period $t$ and node $k$ are, respectively, presented.
$e$	Unit vector.
$\mathbf{Z}_{(kh)in}^t, \mathbf{Z}_{(kh)out}^t$	Regarded as a vector form of two types of connecting variables, the input and the perceived output, the subscript letters have the same meaning as above.
$z_{ok_j}^{(t,t+1)good}, z_{ok_j}^{(t,t+1)bad}$	The vector forms of two types of transition variables, the desired output and the undesired output, respectively, have the same meaning as above.
$s_{ok}^{t-}, s_{ok}^{t+}$	The input and output relaxation variables of $DMU_0$ in the period $t$ and node $k$ are respectively presented.
$\mathbf{s}_{(kh)in}^t, \mathbf{s}_{(kh)out}^t$	Slacks represent two types of connected variables, considered input and deemed output, respectively.
$s_{ok_j}^{(t,t+1)good}, s_{ok_j}^{(t,t+1)bad}$	Slacks represent the two types of transition variables, the desired output and the undesired output, respectively.

Firstly, define the production possibility set as follows:

$$P^t = \left\{ \left( \mathbf{x}_k^t, \mathbf{y}_{ok}^t, \mathbf{z}_{j(kh)}^t, \mathbf{z}_{ok_i}^{(t,t+1)} \right) \mid t = 1, 2, \dots, T \right\} \quad (3)$$

Where each variable satisfies the following constraint conditions:

$$\begin{aligned} & \mathbf{x}_k^t \geq \sum_{j=1}^n \mathbf{x}_{jk}^t \lambda_{jk}^t \quad (\forall k, \forall t) \\ & \mathbf{y}_k^t \geq \sum_{j=1}^n \mathbf{y}_{jk}^t \lambda_{jk}^t \quad (\forall k, \forall t) \\ & \mathbf{z}_{j(kh)}^t \geq, =, \leq \sum_{j=1}^n \mathbf{z}_{j(kh)}^t \lambda_{jk}^t \quad (\forall (kh)_l, \forall l, \forall t) \\ & \text{(Note : as outputs from } k \text{ in period } t) \\ & \mathbf{z}_{j(kh)_l}^t \geq, =, \leq \sum_{j=1}^n \mathbf{z}_{j(kh)_l}^t \lambda_{jh}^t \quad (\forall (kh)_l, \forall l, \forall t) \\ & \text{(Note : as inputs to } h \text{ in period } t) \\ & \mathbf{z}_{k_i}^{(t,t+1)} \geq, =, \leq \sum_{j=1}^n \mathbf{z}_{jk_i}^{(t,t+1)} \lambda_{jk_i}^t \quad (\forall k_i, \forall k, t = 1, 2, \dots, T - 1) \\ & \text{(Note : as carry - over - from } t) \\ & \mathbf{z}_{k_i}^{(t,t+1)} \geq, =, \leq \sum_{j=1}^n \mathbf{z}_{jk_i}^{(t,t+1)} \lambda_{jk_i}^{t+1} \quad (\forall k_i, \forall k, t = 1, 2, \dots, T - 1) \\ & \text{(Note : as carry - over - to } t + 1) \\ & \sum_{j=1}^n \lambda_{jk}^t = 1 \quad (\forall k, \forall t), \lambda_{jk}^t \geq 0 \quad (\forall j, \forall k, \forall t) \end{aligned} \quad (4)$$

The non-radial dynamic network DEA model proposed by Tone and Tsutsui (2014) can be defined as follows:

consistency of data, banks with excessive missing data are excluded, as are banks that are relatively small compared to others of the same ownership type. Ultimately, 140 commercial bank samples are selected, including 6 national-owned commercial banks (NCB), 10 stock commercial banks (SCB), 61 urban commercial banks (UCB), 45 rural commercial banks (RCB), 5 private commercial banks (PCB), and 13 foreign-funded commercial banks (FCB) in mainland China. The specific bank samples can be seen in Table S1 in Supplemental Material. All data collected in this paper are based on the year 2016 and are deflated using the GDP deflator index published by the World Bank to eliminate the impact of price factors.

**Selection of input and output indicators.** The selection of input and output indicators is crucial for effectively assessing the operations efficiency of commercial banks. With respect to the features of the operations process in commercial banks, there is no consensus theory on the choice of these indicators. Currently, the main methods for selecting input-output indicators for assessing the operations efficiency of commercial banks include the production approach, intermediation approach, capital approach, and some niche methods such as value-added approach, portfolio approach, and cash value-added approach. For detailed introductions to these methods, see Zhu et al.

$$\begin{aligned} \min \theta_{ok}^* &= \frac{1 - \frac{1}{m_k + \text{linkin}_k + \text{nbad}_k} \left( \sum_{m=1}^{m_k} \frac{s_{mok}^{t-}}{x_{mok}^t} + \sum_{(kh)_l=1}^{\text{linkin}_k} \frac{s_{o(kh)_l \text{in}}^t}{z_{o(kh)_l \text{in}}^t} + \sum_{k_i^{(t,t+1)}=1}^{\text{nbad}_k} \frac{s_{ok_i^{(t,t+1)} \text{bad}}^{(t,t+1)}}{z_{ok_i^{(t,t+1)} \text{bad}}^{(t,t+1)}} \right)}{1 + \frac{1}{r_k + \text{linkout}_k + \text{ngood}_k} \left( \sum_{r=1}^{r_k} \frac{s_{rok}^{t-}}{x_{rok}^t} + \sum_{(kh)_l=1}^{\text{linkout}_k} \frac{s_{o(kh)_l \text{out}}^t}{z_{o(kh)_l \text{out}}^t} + \sum_{k_i^{(t,t+1)}=1}^{\text{ngood}_k} \frac{s_{ok_i^{(t,t+1)} \text{good}}^{(t,t+1)}}{z_{ok_i^{(t,t+1)} \text{good}}^{(t,t+1)}} \right)} \\ \text{s.t.} & \left\{ \begin{aligned} & \mathbf{x}_{ok}^t = \mathbf{X}_k^t \lambda_k^t + \mathbf{s}_{ok}^{t-} \quad (\forall k, \forall t) \\ & \mathbf{y}_{ok}^t = \mathbf{Y}_k^t \lambda_k^t + \mathbf{s}_{ok}^{t+} \quad (\forall k, \forall t) \\ & \mathbf{e} \lambda_k^t = 1 \quad (\forall k, \forall t) \\ & \mathbf{z}_{o(kh) \text{in}}^t = \mathbf{Z}_{(kh) \text{in}}^t \lambda_k^t + \mathbf{s}_{(kh) \text{in}}^t \quad ((kh) \text{in} = 1, 2, \dots, \text{linkin}_k) \\ & \mathbf{z}_{o(kh) \text{out}}^t = \mathbf{Z}_{(kh) \text{out}}^t \lambda_k^t - \mathbf{s}_{(kh) \text{out}}^t \quad ((kh) \text{out} = 1, 2, \dots, \text{linkout}_k) \\ & \mathbf{z}_{ok_i^{(t,t+1)} \text{good}}^{(t,t+1)} = \sum_{j=1}^n \mathbf{z}_{jk_i^{(t,t+1)} \text{good}}^{(t,t+1)} - s_{ok_i^{(t,t+1)} \text{good}}^{(t,t+1)} \quad (k_i^{(t,t+1)} = 1, 2, \dots, \text{ngood}_k; \forall k; \forall t) \\ & \mathbf{z}_{ok_i^{(t,t+1)} \text{bad}}^{(t,t+1)} = \sum_{j=1}^n \mathbf{z}_{jk_i^{(t,t+1)} \text{bad}}^{(t,t+1)} + s_{ok_i^{(t,t+1)} \text{bad}}^{(t,t+1)} \quad (k_i^{(t,t+1)} = 1, 2, \dots, \text{nbad}_k; \forall k; \forall t) \\ & \lambda_k^t \geq 0; \mathbf{s}_{ok}^{t-} \geq \mathbf{0}; \mathbf{s}_{ok}^{t+} \geq \mathbf{0}; t = 1, 2, \dots, T; o = 1, 2, \dots, n; k = 1, 2, \dots, K \end{aligned} \right. \quad (5) \end{aligned}$$

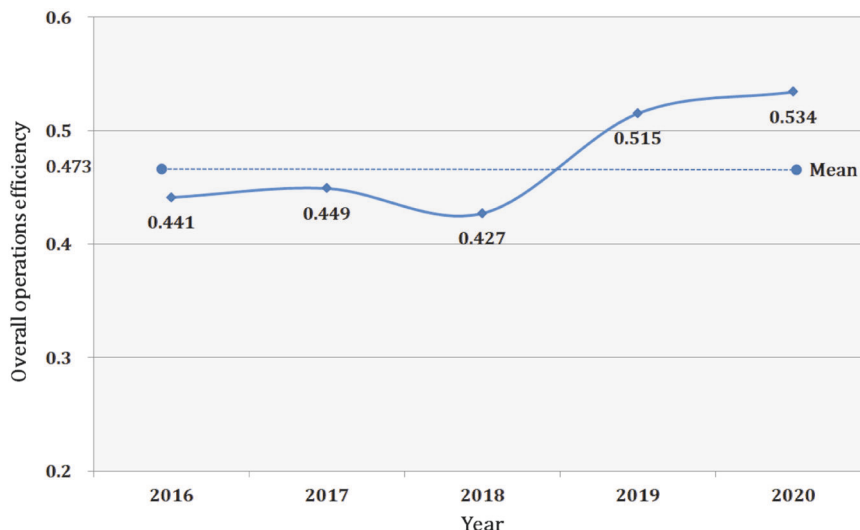
Here  $\theta_{ok}^*$  represents the operations efficiency of DMU<sub>o</sub> in the  $k$ th stage during the period  $t$ . Furthermore, the overall operations efficiency of DMU<sub>o</sub> in the period  $t$  can be obtained as (note: the  $w^k$  represents the stage weight of sub-stage  $k$ ):

$$\eta_o^* = \sum_{k=1}^K w^k \theta_{ok}^* \quad (6)$$

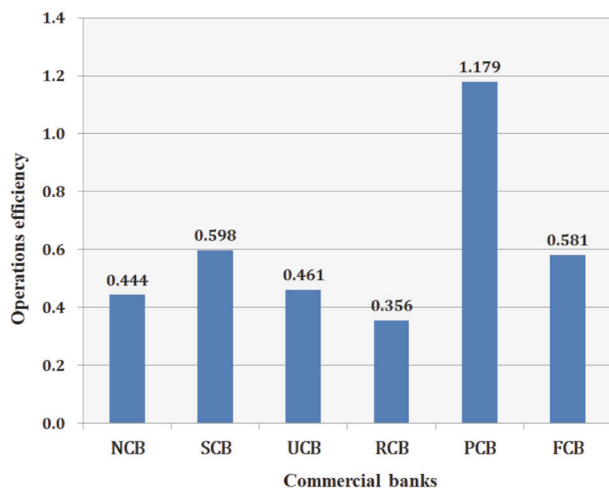
**Assessment and analysis of overall operations efficiency**

**Research samples and data sources.** The data for this paper are sourced from the Wind database, with a few missing data obtained from bank annual reports, BankFocus, or calculated based on annual reports. Considering the availability and

(2021a) and Zhu and Zhu (2023). Although there are many methods for selecting input-output indicators, the mainstream methods are primarily the production approach and intermediation approach. Based on the characteristics of operations process in commercial banks, and the theory of indicator selection, data availability, and existing literature (Liu et al., 2020; Antunes et al., 2021; Zhu et al., 2021a; Nishtha et al., 2022; Wu et al., 2022; Ravanos et al., 2023; Kweh et al., 2024; Takahashi and Vasconcelos, 2024), this paper selects the following input indices: owner’s equity ( $X_1$ ), labor cost ( $X_2$ ), and operating expenses ( $X_3$ ). The expected output indices include net interest income ( $Y_1$ ), fee charges and commission income ( $Y_2$ ), and net investment income ( $Y_3$ ), while the undesirable output indicator is non-performing loans ( $B_1$ ).



**Fig. 1 Overall trend of operations efficiency of six types of commercial banks in China.** This figure shows the trend of overall operations efficiency of Chinese commercial banks from 2016 to 2020. Although the overall operational efficiency was relatively low during the period, it has maintained a growth trend.



**Fig. 2 Comparative analysis of operations efficiency of six types of commercial banks in China.** This bar graph compares the overall operations efficiency of six types of Chinese commercial banks with different ownership from 2016 to 2020. There exists a significant divergence among different ownership types, which reflects the significant differences in their operating levels. Besides, private banks performed best among the five types of domestic banks, and rural banks performed the worst.

**Descriptive statistical analysis.** This paper used SPSS software for descriptive statistical analysis of input-output variables, with detailed results shown in Table S2 in Supplemental Material. (Note: new variables appearing in the following text are also included in this table for statistical analysis). Units for all variables are in ten thousand CNY. The descriptive statistical results show that there is a very large range and standard deviation among the various indicator variables, indicating significant differences and non-uniformity among the input-output variables of different types of commercial banks. As can be seen from the results of descriptive statistical analysis, except for fee and commission income and net investment income (which may have been affected by the COVID-19 pandemic in 2020), labor costs, owner’s equity, operating expenses, total loans, total investments,

and net interest income of commercial banks in China have all maintained a continuous growth trend during the 13th Five-Year Plan period. Additionally, the scale of non-performing loans of commercial banks also showed a continuous upward trend during the study period.

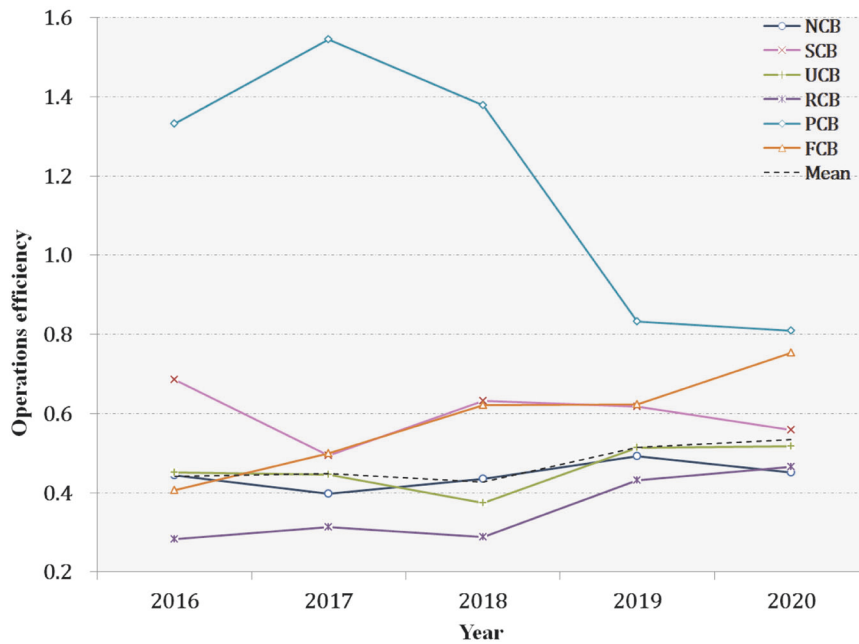
**Analysis of efficiency measurement results.** The operations efficiency of different ownership types of Chinese commercial banks during the 13th Five-Year Plan period was measured using the super-efficiency SBM-DEA model with undesirable output proposed by Zhu and Zhu (2023). Measurement results can be obtained by contacting the corresponding author. To visually display the research results, please see the following Figs. 1–3.

As shown in Fig. 1, although the overall operations efficiency of different ownership types of Chinese commercial banks was low (mean value = 0.473) during the study period, the operations efficiency of commercial banks maintained a continuous upward trend (Note: only in 2018 the operations efficiency slightly decreased compared to 2017, possibly due to the large-scale trade friction that erupted in 2018), with an average annual increase of about 5.27 percentage. In 2020, operations efficiency increased by about 21.09 percentage compared to 2016.

Figure 2 reflects the comparative operations efficiency of different ownership types of Chinese commercial banks. The results show that the operations efficiency of commercial banks in China, from high to low, is as follows: private banks, joint-stock banks, foreign banks, urban banks, state-owned banks, and rural banks. It can also be seen that there is a significant divergence in the operations efficiency of different ownership types of commercial banks, with private banks performing the best (1.179) and rural banks performing the worst (0.356).

Figure 3 reflects the changing trend of the operations efficiency of different ownership types of Chinese commercial banks over different years in the study period. As shown in Fig. 3, the following conclusions can be drawn:

- (1) The operations efficiency of various ownership types of commercial banks in China in different years shows obvious non-uniformity, but this non-uniformity has a gradually narrowing trend.
- (2) Private banks have the best operations efficiency each year, far surpassing state-owned banks, joint-stock banks, urban



**Fig. 3 Trend of operations efficiency of six types of commercial banks in China.** This figure illustrates the trend of annual operations efficiency of six types of Chinese commercial banks with different ownership from 2016 to 2020. During the period, the operations efficiency of foreign banks, urban banks, and rural banks increased, while that of state-owned banks remained stable. In contrast, the private banks and joint-stock banks declined.

banks, rural banks, and foreign banks. In addition, the annual operations efficiency of private banks shows a continuous downward trend, with a significant regression in 2020 compared to 2016.

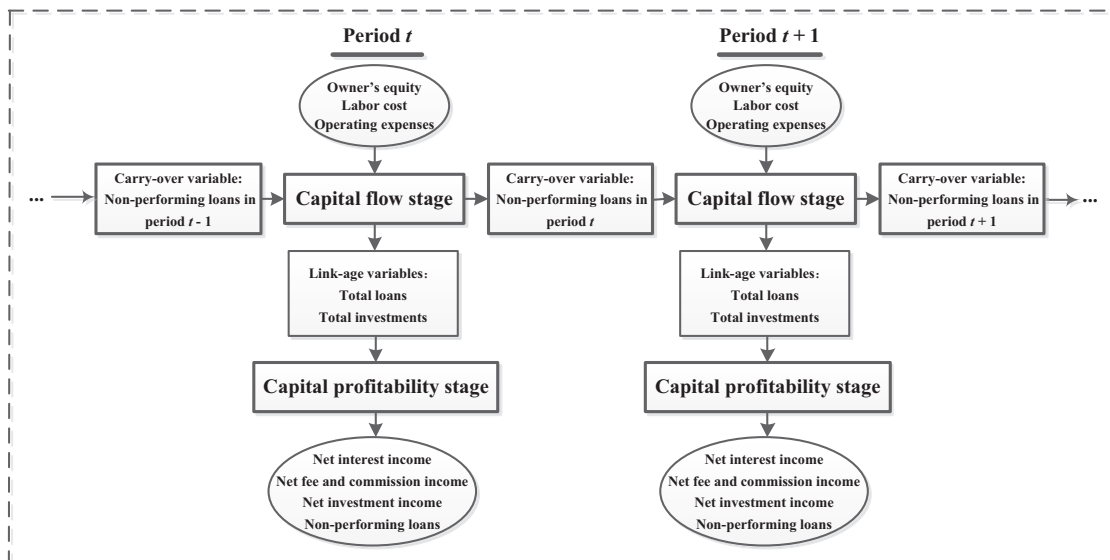
- (3) Foreign banks perform well in terms of annual operations efficiency, but their annual operations efficiency shows a stable upward trend, continuously improving. The annual operations efficiency of foreign banks in 2020 has increased significantly compared to 2016, almost catching up with the best-performing private banks.
- (4) The level of annual operations efficiency of joint-stock banks is on par with that of foreign banks, overall performing well, but there is a slight decline in 2020 compared to 2016.
- (5) State-owned banks, urban banks, and rural banks generally perform poorly in terms of annual operations efficiency. State-owned banks show an almost stable trend in annual operations efficiency, while urban banks and rural banks show a slight increase in annual operations efficiency in 2020 compared to 2016.

In summary, the overall operations efficiency of foreign banks, urban banks, and rural banks has improved during 2016–2020. The improvements in the operations efficiency of foreign banks may be related to the continuous expansion of the Chinese financial sector opening up to the world, with a series of policies favorable to the operation of foreign-controlled banks in China being implemented. Additionally, although urban banks and rural banks have relatively low overall operations efficiency, they have maintained steady growth. The reason for the sustained growth in the operations efficiency of rural banks may be that, with the continuous development of China’s rural revitalization, China’s investment in the field of construction of new socialist countryside has been increasing, and at the same time the reform in the field of rural financial sector has been deepened, so that the rural banks have reaped great opportunities for growth in the field of rural financial sector, due to its institutional advantages and customer market advantages. The reason for the growth in operations efficiency of urban banks is like that of rural banks,

which is also related to favorable policies in the industry. State-owned banks are the ones whose operations efficiency remains stable, which is more in line with Chinese conditions due to their large capital size and high social status. Private banks and joint-stock banks are the ones whose operations efficiency declined during the study period. Therefore, although private banks have the best overall performance in terms of operations efficiency (1.179), the momentum is starting to weaken, and there is a significant decline in operations efficiency in 2020 compared to 2016. The reason for this may be due to the late start of private banks, the previous accumulation of non-performing loans did not appear in the previous years, but due to the sudden outbreak of COVID-19 in 2020 resulting in a concentration of non-performing loans, which in turn negatively affected their operations performance.

**Operations efficiency decomposition and analysis**

**Complex dynamic network structure for operations process in commercial banks.** Considering the complexity and continuity of the operations process in commercial banks, the dynamic network DEA model is known to be helpful under this context and has attracted extensive attention to investigate the operations efficiency of different sub-stages in banking activities. Existing literature has already attempted to open the “black box” of China’s banking operations process from various perspectives, and devoted substantial contributions to the assessment of internal operations efficiency of commercial banks. Previous studies generally divided the operations process of commercial banks into two or three sub-stages (Yeh et al. 2022; Panwar et al. 2022). The first stage is the fundraising stage (namely the deposit attraction stage), where banks obtain deposits from the public with relatively low-interest expenses. The second stage is the liability allocation stage (namely the fund operation stage), where banks allocate customer deposits, which are essentially liabilities, through mortgages, investments, and intermediary services. The third stage is the capital profitability stage, where banks earn interest income, fees and commission income, and investment returns from the operations of the previous stages. Furthermore,



**Fig. 4 Complex dynamic network structure for operations process of commercial banks.** This diagram illustrates a new two-stage dynamic network structure for the internal operations process of commercial banks. It's first subdivided into two-stage network structure, namely capital flow and capital profitability stage, and the non-performing loans are used as a carry-over variable connecting two adjacent periods in the first stage.

in view of the inter-period connections in the operations process of commercial banks, existing literature often used some variables such as non-performing loans and undistributed profits as carry-over variables connecting two adjacent periods, thus addressing the shortcomings of the network DEA method in ignoring the link between the production activities of banks in different periods.

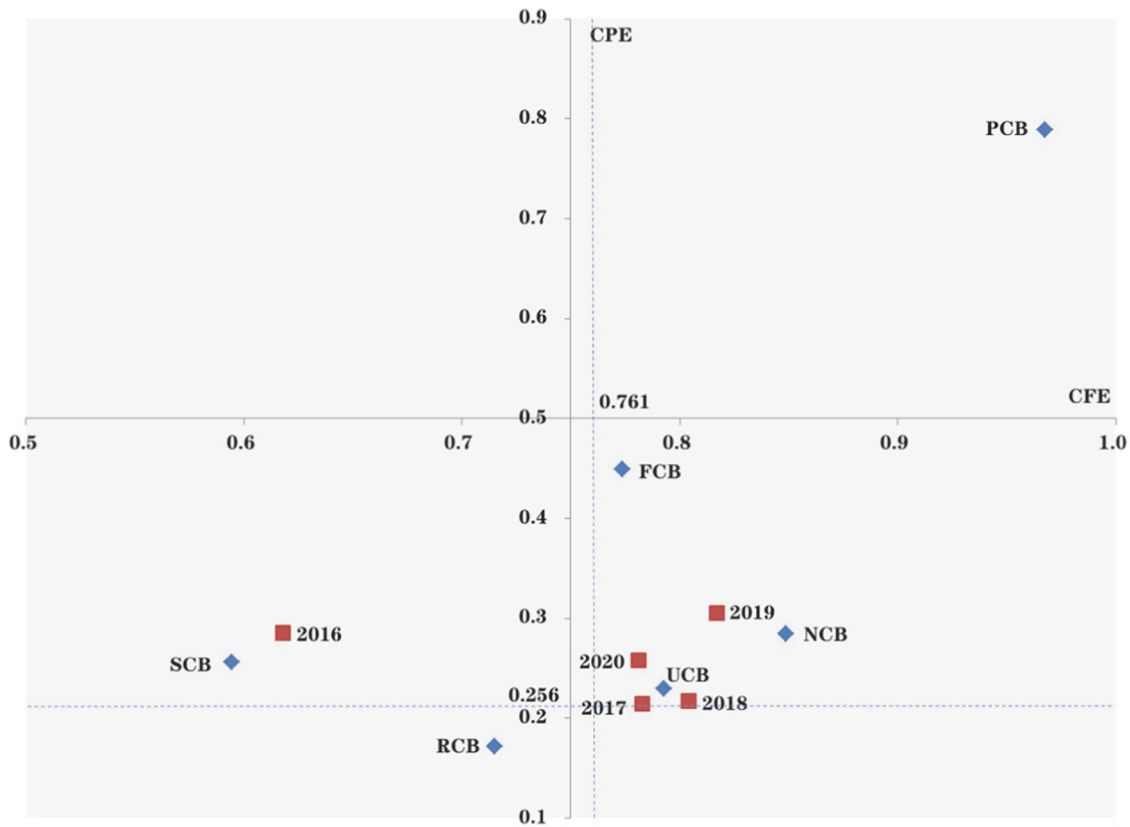
Based on previous research, this paper divides the internal operations process of commercial banks into two stages from the perspectives of bank development capability, liquidity, safety, and profitability. The dynamic network structure is illustrated in Fig. 4. This network structure has the following characteristics. The first stage is the capital flow stage, with input variables being owner's equity, labor cost, and operating expenses, and output variables being total loans and total investments. The second stage is the capital profitability stage, where total loans and total investments are input to achieve expected outputs like net interest income, net fee and commission income, and net investment income, as well as undesirable outputs like current non-performing loans. Total loans and total investments serve as carry-over variables connecting the first and second stages, while the non-performing loans of the previous period act as linkage variables connecting the first stage between periods  $t-1$  and  $t$ , thus incorporating the lagged impacts of previous non-performing loans on bank operations into the model.

Compared to previous literature, the network structure constructed in this paper combines the deposit attraction and liability allocation stages of commercial banks into one capital flow stage. The process from deposit attraction to liability allocation is essentially the continuous flow of funds in operations, making this classification more aligned with the internal operations processes of commercial banks. Additionally, previous studies often share inputs from the first stage in the second or third stage, but the actual utilization rate of the first stage's inputs in the subsequent stages is hard to ascertain. Directly treating them as fully utilized could lead to biased measurement results. Therefore, the classification in this paper also helps in the rational selection of input-output indicators for each stage. Finally, the network structure in this paper considers the lagged impact of previous non-performing loans in the capital flow stage, and includes current non-performing loans as an

undesirable output in the capital profitability stage, making the model's measurement structure more reasonable.

**Selection of input-output indicators.** Based on the detailed description of the internal operations process of commercial banks in the previous section, the selection of input-output indicators for the multi-stage dynamic DEA model in this paper considers the theory of indicator selection, the division of operations stages in commercial banks, data availability, and existing literature (Ebrahimnejad et al. 2014; Chen et al. 2018; Zhou et al. 2018; Fukuyama, et al. 2020; Henriques et al. 2020; Lartey et al.,2021; Khoveyni and Eslami, 2021; Li et al. 2022; Yang, 2023; Kweh et al. 2024). The specific indicators for each stage are as follows: The input variables for the capital flow stage are owner's equity ( $X_{11}$ ), labor cost ( $X_{12}$ ), and operating expenses ( $X_{13}$ ); output variables are total loans ( $C_{11}$ ) and total investments ( $C_{12}$ ). The input variables for the capital profitability stage are total loans ( $C_{11}$ ) and total investments ( $C_{12}$ ), with expected outputs being net interest income ( $Y_{21}$ ), fee charges and commission income ( $Y_{22}$ ), and net investment income ( $Y_{23}$ ), and the undesirable output being current non-performing loans ( $B_{21}$ ). Total loans ( $C_{11}$ ) and total investments ( $C_{12}$ ) are regarded as carry-over variables connecting the first and second stages, while previous period non-performing loans ( $L_{11}$ ) act as linkage variables connecting the first stage between period  $t-1$  and period  $t$ . Data sources, units, and preprocessing methods for these indicators are the same as previously mentioned and are not reiterated here.

**Efficiency decomposition results and analysis.** Currently, the non-radial dynamic network DEA model proposed by Tone and Tsutsui (2014) is the mainstream method for efficiency evaluation in the banking sector and other fields and has received extensive support and expansion from numerous scholars (Wanke et al. 2016; Zhou et al. 2018). Therefore, based on the dynamic two-stage network structure of the internal operations process of commercial banks constructed in this paper (as shown in Fig. 4), the model proposed by Tone and Tsutsui (2014) is applied to structurally decompose the operations efficiency of various ownership types of commercial banks in China during the 13th Five-Year Plan period. Due to space limitations, the measurement



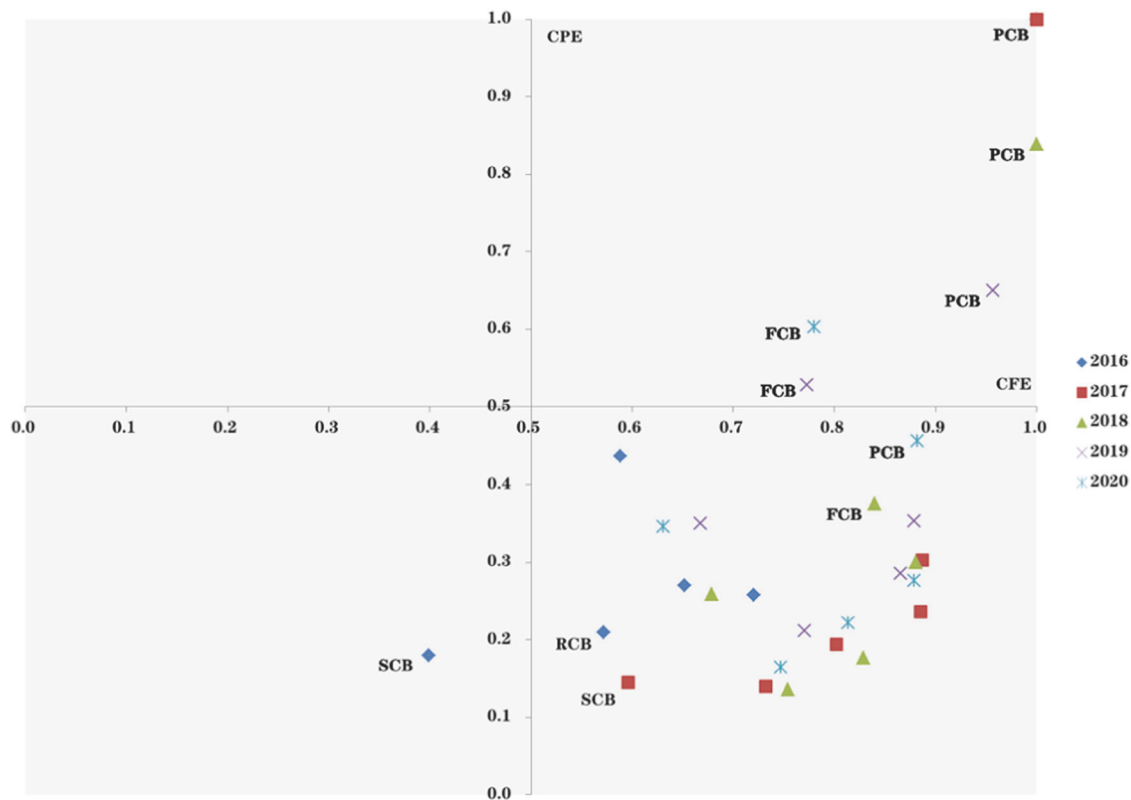
**Fig. 5 Overall comparison of CFE and CPE of six types of commercial banks in China.** This figure compares the results of overall operations efficiency decomposition of six types of Chinese commercial banks with different ownership during 2016–2020. The capital flow efficiency is significantly better than capital profitability efficiency, and the main internal cause of low efficiency in banking sector is the inadequacy of capital profitability.

results are not directly displayed but can be obtained by contacting the corresponding author.

The measurement results of operations efficiency decomposition for commercial banks with different ownership types are presented in Fig. 5, and the following conclusions can be drawn:

- (1) During the study period, the average capital flow efficiency (CFE) of various types of commercial banks in China was 0.761, while the average capital profitability efficiency (CPE) was 0.256. This indicates that the internal reason for the inefficiency of various ownership types of commercial banks in China is mainly due to insufficient efficiency of capital profitability.
- (2) Private banks performed the best in both capital flow efficiency and capital profitability efficiency. Following them are foreign banks and state-owned banks, where foreign banks excelled in capital profitability efficiency, and state-owned banks excelled in capital flow efficiency. The worst-performing banks were urban commercial banks, joint-stock banks, and rural commercial banks, with very low capital profitability efficiency, but urban commercial banks had a significantly higher capital flow efficiency than joint-stock and rural commercial banks, even slightly surpassing foreign banks.
- (3) Although there was a slight decline in capital profitability efficiency among various ownership types of commercial banks, there was a significant improvement in capital flow efficiency. However, considering the impact of the COVID-19 pandemic in 2020, if we look from 2019, compared to 2016, the capital profitability efficiency still shows a slight increase, and the capital flow efficiency has improved even more.

The following analysis can further examine the changes in capital flow efficiency and capital profitability efficiency during the study period, as well as the efficiency differences between different ownership types of commercial banks, from both time and sample perspectives. From Fig. 6, we can see that the internal reason for the operations inefficiency of commercial banks is mainly manifested as insufficient efficiency of capital profitability. In 2016, there was a significant divergence in the operations efficiency of various ownership types of commercial banks, with private banks performing the best in both capital flow efficiency and capital profitability efficiency. Joint-stock banks performed the worst, ranking last in two stages. From an overall perspective, the operations efficiency was relatively poor in 2016, with both capital flow efficiency and capital profitability efficiency being low. In 2017, the situation improved compared to 2016, mainly due to improvements in capital flow efficiency, but capital profitability efficiency remained low. In 2017, there was also a significant divergence in operations efficiency, with private banks performing the best in both capital flow efficiency and capital profitability efficiency. Joint-stock banks performed the worst, ranking last in two stages. In 2018, the overall results for the two years were not significantly different compared to 2017, with private banks still performing the best and state-owned banks and rural banks performing poorly (mainly manifested as insufficient efficiency of capital profitability). In 2019, the overall capital profitability efficiency has improved compared to 2018. In 2020, there was a significant divergence in the operations efficiency compared to 2019, with poorly performing banks showing poor performance in both capital flow efficiency and capital profitability efficiency that year.



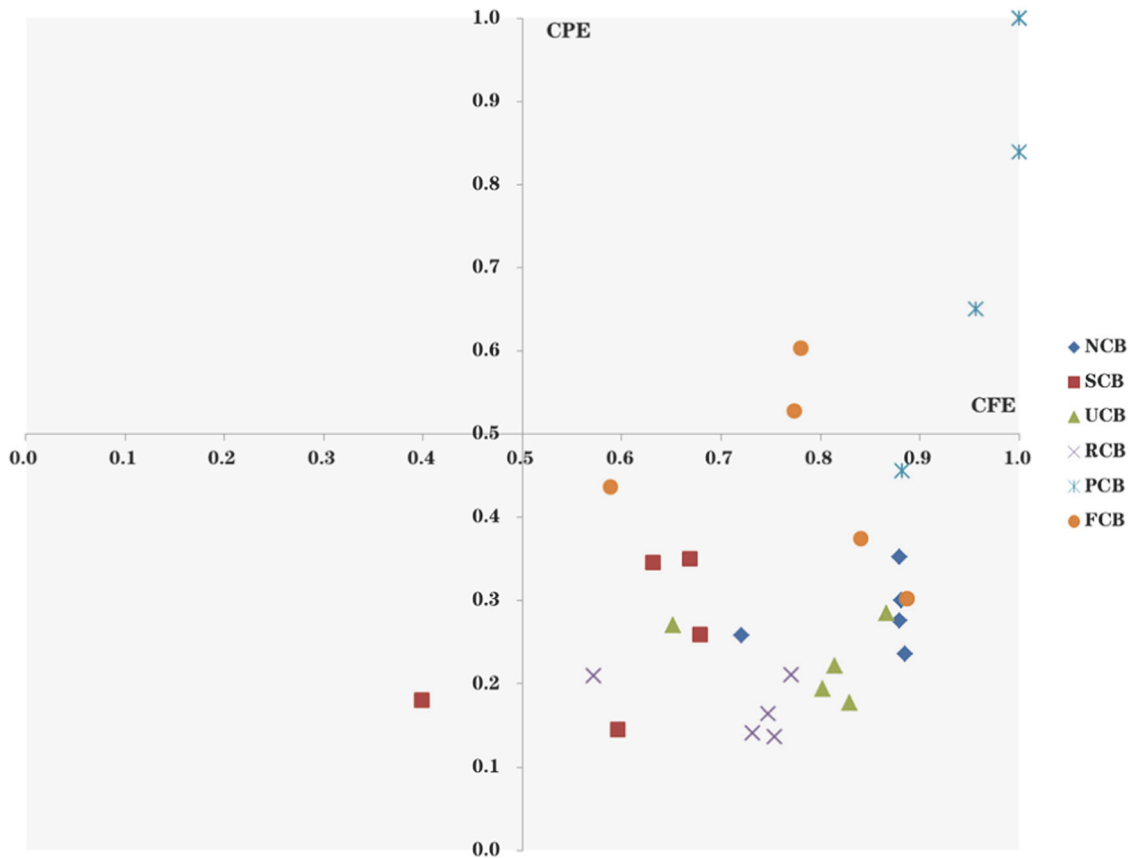
**Fig. 6 Comparison of CFE and CPE of commercial banks in China by year.** This figure compares the results of annual operations efficiency decomposition of six types of Chinese commercial banks with different ownership. The internal reason for inefficiency of Chinese commercial banks is mainly manifested as insufficient efficiency of capital profitability.

As shown in Fig. 7, from the perspective of different ownership types of bank samples, it is still evident that the internal reason for the overall operations inefficiency of commercial banks in China is mainly due to insufficient capital profitability efficiency. Overall, private banks and foreign banks performed the best, excelling in both capital flow efficiency and capital profitability efficiency, but their performances varied significantly in different years. What's more, state-owned banks, joint-stock banks, urban banks, and rural banks showed varying performances in different years, with their capital flow efficiency generally better than capital profitability efficiency. Their internal reason for operations inefficiency is mainly due to low capital profitability efficiency, and they also showed some divergences in performance in different years.

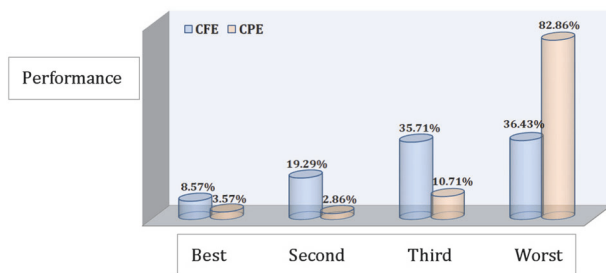
Finally, 12 commercial banks (8.57% of the sample) performed the best in capital flow efficiency (efficiency value of 1); 27 commercial banks (19.29% of the sample) performed well (efficiency value between 0.9 and 1); 50 commercial banks (35.71% of the sample) performed averagely (efficiency value between 0.7 and 0.9); and 51 commercial banks (36.43% of the sample) performed poorly (efficiency value below 0.7). In terms of capital profitability efficiency, 5 commercial banks (3.57% of the sample) performed the best (efficiency value of 1); 4 commercial banks (2.86% of the sample) performed well (efficiency value between 0.7 and 1); 15 commercial banks (10.71% of the sample) performed averagely (efficiency value between 0.4 and 0.7); and 116 commercial banks (82.86% of the sample) performed poorly (efficiency value below 0.5). Additionally, the Industrial and Commercial Bank of China, Zhejiang Qianhai WeBank, and Wenzhou Minshang Bank performed the best in both capital flow efficiency and capital profitability efficiency. These measurement results are shown in Fig. 8 to

visually reflect that the capital flow efficiency was significantly better than capital profitability efficiency, and about 80% of commercial banks have problems with relatively poor capital profitability efficiency.

**Statistical tests.** According to the above analysis, there exists a significant divergence among commercial banks in China with different ownership types, which reflects the significant differences in their operating levels, but whether this finding is statistically significant needs a statistical test. Generally, the statistical tests include parametric and non-parametric tests. The parameter test is a method of inferring parameters like mean or variance of the overall distribution when the form of population distribution is known. However, in the process of data analysis, people often cannot make simple assumptions about the overall distribution pattern for various reasons, and the method of parameter verification is no longer applicable. By contrast, the nonparametric test is a method based on this consideration, which uses the sample data to infer the form of population distribution, when the population variance is unknown or little known. Since the nonparametric test method does not involve parameters related to the overall distribution in the inference process, it is called the nonparametric test. The Kruskal–Wallis rank test is a widely used nonparametric test method, it compares the rank of two or more samples, and it is essentially a generalization of the Wilcoxon rank sum test method for two samples. The basic principle of the Kruskal–Wallis rank test is to use the sum of the squares of the groups divided by the total sample rank variance to construct the Kruskal–Wallis  $H$  test statistic as a powerful basis for determining whether there is a difference between the groups. More information and applications about the Kruskal–Wallis rank test can be seen in Kruskal and Wallis



**Fig. 7 Comparison of CFE and CPE of six types of commercial banks in China.** This figure compares the results of operations efficiency decomposition of six types of Chinese commercial banks with different ownership from the individual perspective. It also reveals that the internal reason for inefficiency of Chinese commercial banks is mainly manifested as insufficient efficiency of capital profitability.



**Fig. 8 Overall proportional comparison of CFE and CPE for all samples.**

This figure compares the overall proportion of capital flow efficiency and capital profitability efficiency for all research samples. It reflects that about 80% of Chinese commercial banks have relatively poor capital profitability efficiency.

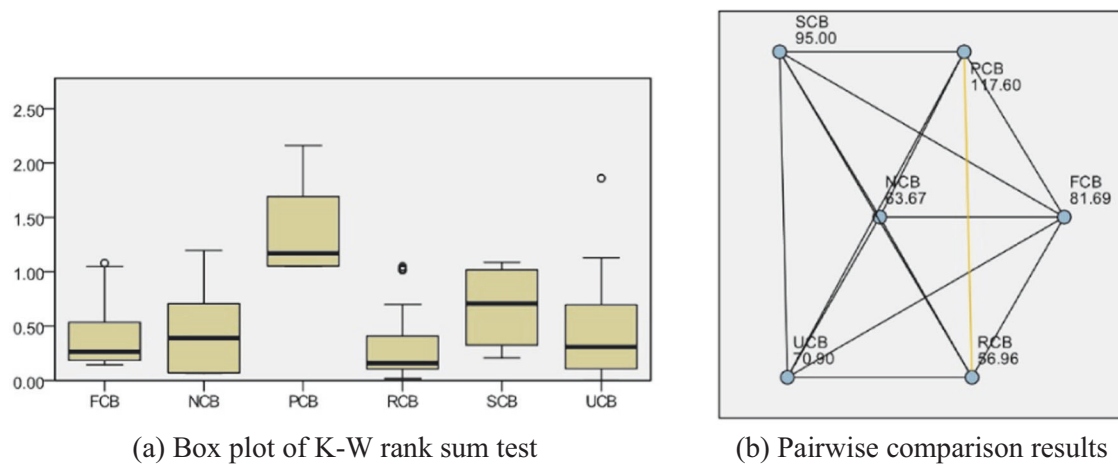
(1952), Sueyoshi and Aoki (2001), Zhu et al. (2021a), and Zhu and Zhu (2023).

Results of the Kruskal–Wallis rank-sum test using SPSS software are shown in Fig. 9, we can see that the Kruskal–Wallis *H* test statistic for the overall operations efficiency of various types of commercial banks in China during the study period is 16.577, approximated using a chi-square distribution with 5 degrees of freedom, resulting in a probability greater than the chi-square test critical value of 11.07 of 0.005. (Note: The test statistic has been adjusted for ties; the significance level is 0.05.) Therefore, the Kruskal–Wallis rank-sum test for the overall operations efficiency rejects the null hypothesis, which indicates that the overall distribution of operations efficiency of different

ownership types of commercial banks is statistically significant, and thus there is a significant difference in overall operations efficiency among different ownership types of commercial banks in China during the study period.

Additionally, as can be seen from the box plot in Fig. 9a, the median overall operations efficiency was markedly different. Private banks had a significantly higher median operations efficiency compared to other ownership types of banks, further confirming the characteristic non-uniformity in overall operations efficiency. On the other hand, the overall operations efficiency of the same ownership type of banks also varied to different extents across different years, which indicates that even within the same ownership type of banks, there is non-uniformity in overall operations efficiency. However, this non-uniformity tended to increase in private, foreign, and rural commercial banks, while it tended to decrease in state-owned, joint-stock, and urban commercial banks. Therefore, there were significant differences and typical non-uniform characteristics in the overall operations efficiency among different ownership types of commercial banks, and among different bank samples of the same ownership type, which are mainly influenced by factors like national strategy, regional location, resource endowment, management level, operations concept, and financial technology level.

Since the Kruskal–Wallis rank sum test yielded a *P*-value of <0.05, indicating statistical significance in the differences between at least two groups, pairwise comparisons are necessary. This study used SPSS software for pairwise comparisons, and the results are shown in Fig. 9b. It can be seen that there is a statistically significant difference in the overall operations efficiency between private banks and rural commercial banks



**Fig. 9 Results of Kruskal-Wallis rank sum test. a** Box plot of K-W rank-sum test. **b** Pairwise comparison results. This figure shows the results of Kruskal-Wallis rank-sum test for the overall operations efficiency. It indicates that the overall distribution of operations efficiency of different ownership types of Chinese commercial banks is statistically significant.

during the entire 13th Five-Year Plan period. To reduce Type I errors, adjusted probabilities were calculated using SPSS software. The calculation results confirm that the aforementioned conclusions are still valid, i.e., the adjusted significance  $P$ -value remains less than 0.05 (Note: Due to space limitations, the specific calculation results of the adjusted probabilities are not shown here, but interested readers can contact the corresponding author for more information.)

The Kruskal-Wallis rank sum test results for the CFE and CPE of different ownership types of commercial banks are shown in Table 2. Here both the Kruskal-Wallis  $H$  statistic and the  $P$ -values indicate that the hypothesis of homogeneity in CFE is rejected for each year from 2016 to 2020 and for the entire study period, which implies that there are statistically significant differences in the CFE. Similarly, significant differences are also evident in the CPE.

### Conclusions and managerial implications

This study explored the operations efficiency and decomposition of the banking sector in the Chinese mainland and conduct a comparative analysis on domestic and foreign commercial banks with different ownership types. The operations efficiency of various ownership types of commercial banks during the 13th Five-Year Plan period was measured using a super slacks-based measure DEA model with undesirable outputs. Results show that although the overall operations efficiency of commercial banks was low, there was a consistent and steady increase in operations efficiency. Moreover, a significant divergence in operations efficiency was observed among different ownership types of commercial banks, with the efficiency ranking from highest to lowest being private banks, stock banks, foreign banks, urban banks, state-owned banks, and rural banks. One weakness of a super slacks-based measure DEA model is the omission of the internal structure of DMUs. To measure the division efficiency of internal structures of DMUs, we further constructed a novel complex dynamic network structure for the internal operations process of banks. Here, it is subdivided into a two-stage network structure, namely capital flow and capital profitability stage, with non-performing loans used as a carry-over variable connecting the first stage of two adjacent periods, to give the internal explanations for the root causes of inefficiency.

To assess the division efficiency of the capital flow stage and capital profitability stage, we utilize a dynamic slacks-based

DEA model with network structure to decompose the operations efficiency of banks into two constituent components, namely CFE and CPE. Here, this technique proposed by Tone and Tsutsui (2014) allows for the evaluation of both the overall efficiency of DMUs and the efficiency of their internal divisions. Specifically, the analysis periods are connected through carry-over variables, and the divisions are connected by link-age variables. Recently, this technique has been used in several studies involving efficiency analysis in banking, education, environment, healthcare, transportation, manufacturing, energy and so on (Emrouznejad and Yang, 2018; Kweh et al. 2024). In outline, the decomposition efficiency calculated using a dynamic slacks-based DEA model with network structure is noted as one of the highly preferable aspects highlighted in this study. Assessment results indicate that the CFE of commercial banks was significantly better than CPE, with the main internal cause of inefficiency in operations being the inadequacy of capital profitability. Besides, there is a large gap in the operating performance (namely capital flow efficiency or capital profitability efficiency) of commercial banks with different ownership types, which reflects the significant differences in their operating levels.

The findings of this study reveal that domestic and foreign-funded commercial banks in the Chinese mainland are facing a performance threshold geared by the distinctive nature of different banking ownership types, whether foreign-funded or Chinese national-owned banks. Overall, foreign-funded banks performed better than Chinese-funded banks on average during 2016–2020. Besides, there exists a significant divergence in the overall operations efficiency, capital flow, and profitability efficiency among banks with different ownership types, which reflects the significant differences in their operating levels. This imbalance trend is not only reflected among banks with different ownership types, but also among different banks of the same ownership type. Therefore, it is necessary to narrow the gap in competitiveness and sustainable development levels among various ownership banks and achieve balanced development goals. Moreover, private banks performed best among the five types of domestic banks, and rural banks performed the worst. The business operation of private banks usually presents higher leveraged loan activities and therefore better capital profitability efficiency, the more aggressive financial principles in private banks may be contributing to a faster pace in deposit attraction, liability

**Table 2 Kruskal-Wallis rank sum test results for CFE and CPE.**

	2016		2017		2018		2019		2020		2016-2020	
	CFE	CPE	CFE	CPE	CFE	CPE	CFE	CPE	CFE	CPE	CFE	CPE
K-W statistic	22.75	20.80	18.20	29.53	29.67	20.03	16.09	25.33	23.82	20.48	28.49	30.08
P-value	0.000	0.001	0.003	0.000	0.000	0.001	0.007	0.000	0.000	0.001	0.000	0.000

① The total number of observational samples is 140, with the samples for state-owned banks, joint-stock banks, private banks, and foreign banks being 6, 10, 61, 45, 5, and 13, respectively.  
 ② Degrees of freedom: 5, with the corresponding chi-square critical value being 11.07.  
 ③ P-value with a significance level of 0.05 and a 2-sided test.  
 ④ The test statistics have been adjusted for correction factors.

allocation and equity generation when compared to other Chinese domestic banks.

Additionally, the capital flow efficiency was significantly better than capital profitability efficiency, and the main internal cause of low efficiency in the banking sector is the inadequacy of capital profitability. It reveals that banks operating in China should manage their capital profitability effectively to enhance overall operations performance. During the capital profitability stage, commercial banks primarily derive outputs like net interest income, net fee and commission income, net investment income, and non-performing loans by leveraging their total loans and total investments. To optimize these outcomes, banks must capitalize on their existing shareholder resources, customer base, third-party collaborations, and sales channels. This strategic utilization should be directed towards crafting a diversified business approach, which in turn will steadily grow fee-based services, commission-based offerings, investment activities, and currency exchange operations, thereby broadening the spectrum of non-interest income sources. Meanwhile, banks should focus on minimizing both interest and non-interest expenses. This can be achieved by expanding the scale of net interest income and loan operations, which may involve diversifying financing avenues, engaging private financial entities, enhancing credit product innovation, and enriching the array of financial products and services available.

It is also worth pointing out that some proactive measures, like a continuous improvement of both internal and external risk control mechanisms, bolstering risk management frameworks, and reinforcing the overall risk management system infrastructure, are essential to mitigate the adverse effects of non-performing loans. To further disperse these operational risks, banks can adopt a range of strategies such as financing agency arrangements, equity partnerships, joint financing initiatives, and syndicated lending. These diversified approaches will not only help in reducing the incidence of non-performing loans but also in enhancing the bank's financial stability and resilience in the face of market fluctuations. Through these comprehensive strategies, banks can enhance their profitability and strengthen their competitive edge in the financial marketplace. Specifically, some managerial implications to enhance the operations efficiency of China's banking industry from a risk management perspective can be adopted, like enhancing the awareness of risk value creation, improving the level of risk quantification, refining risk management mechanisms, and strengthening financial technology innovation.

Although some valuable insights on operations efficiency and the decomposition efficiency of commercial banks in China with different ownership types using the new research framework proposed in this study, there are still some limitations. Future directions can be conducted from the following aspects. For instance, some banks are not included in the research samples because of the lack of available data, which may cause biased results. Further study should collect more bank samples, researchers may select a new context to check the results, or they may also take a new study and change the framework to check the existing DEA approaches to address this gap. What's more, traditional DEA approaches assess efficiency according to input/output data, which do not provide information on estimating the amount of inputs and/or outputs needed to achieve efficiency targets (Emrouznejad and Amin, 2023). Further studies can utilize inverse DEA models to compare and validate their measurement results with this study. Finally, the proposed framework in this study is applicable in many similar scenarios like government agencies, airlines, healthcare, transportation, education, financial institutions, and manufacturing companies, etc. Readers interested can further expand this new research framework to the

case of various scenarios prove whether it is still useful, and explore more worthy and promising findings for different fields.

### Data availability

The data used in this paper will be available on request, please contact the corresponding author.

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### Notes

- 1 Here the “black box” is a metaphorical description and refers to the internal process of DMU’s production and operation activities. Opening the “black box” refers to dividing the internal production and operation activities of DMU’s into multiple stages for research, thereby separately calculating the efficiency of each sub-stage and the overall efficiency of DMUs. However, based on the characteristics of the DEA method, when calculating the efficiency of sub-stages, the sub-stages are still considered as a “black box”. Therefore, opening the “black box” is defined relative to the perspective of the overall production and operation activities of DMUs, while from the perspective of the sub-stages of DMU’s production and operation activities, it is still not opening the “black box”. For this note, the authors would like to express acknowledgments to Professor Hong Yan.
- 2 The exponential decay model refers to the impact of DMU’s efficiency in different periods on its overall efficiency value changing over time, similar to the exponential decay in physics and chemistry. This change is ultimately reflected through the weights of each period, which are generally defined according to the proximity of the period to the research time. The closer the period is to the research time, the greater its impact, and the further away the period is, the weaker its impact and the smaller the weight, according to Zha et al. (2016).

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### Author contributions

Chuanjin Zhu: Writing-original draft and editing and software. Rui Wang: Writing review and editing, data curation, and investigation.

### Competing interests

The authors declare no competing interests.

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Ethical approval was not required as the study did not involve human participants.

### Informed consent

This article did not involve human participants and no informed consent was required.

### Additional information

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