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Research Article

An Eco-Inefficiency Dominance Probability Approach for Chinese Banking Operations Based on Data Envelopment Analysis

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Data envelopment analysis (DEA) has proven to be a powerful technique for assessing the relative performance of a set of homogeneous decision-making units (DMUs). A critical feature of conventional DEA approaches is that only one or several sets of optimal virtual weights (or multipliers) are used to aggregate the ratio performance efficiencies, and thus, the efficiency scores might be too extreme or even unrealistic. Alternatively, this paper aims at developing a new performance dominance probability approach and applying it to analyze the banking operations in China. Towards that purpose, we first propose an extended eco-inefficiency model based on the DEA methodology to address banking activities and their possible relative performances. Since the eco-inefficiency will be obtained using a set of optimal weights, we further build a performance dominance structure by considering all sets of feasible weights from a data-driven perspective. Then, we develop two pairwise eco-inefficiency dominance concepts and propose the inefficiency dominance probability model. Finally, we illustrate the eco-inefficiency dominance probability approach with 32 Chinese listed banks from 2014 to 2018 to demonstrate the usefulness and efficacy of the proposed method.

1. Introduction

Forty years have gone by since the great reform and opening policy of 1978, and China has made substantial progress in economic development with an annual increase of almost nine percent in gross domestic product from 149.541 billion dollars in 1978 to 13.608 trillion dollars in 2018. It is rather remarkable that the banking industry of China, especially state-owned and listed banks, has played a great role in Chinese economic growth [1, 2]. Throughout the ever-increasing national economic development, the banking industry in China has also been promoted and developed considerably. For example, the total assets of the Chinese banking industry reached almost 41 trillion dollars in 2018, which is more than three times the gross domestic product in current US dollars in the same year. Meanwhile, the unprecedented competition within Chinese banks and between Chinese domestic banks and foreign banks has become increasingly fierce since the opening of financial markets. To participate in the ongoing competitive challenges all over the world, it is of vital importance for Chinese banks to pay special attention to their operation performances [1, 3, 4]. In addition, it is also an inherent requirement of guaranteeing and promoting the healthy and sustainable economic development of China to address the banking performance.

Among the family of existing performance evaluation methods, data envelopment analysis (DEA) is one of the major approaches because of its general applicability [5–10]. DEA, first introduced by Charnes et al. [11] and further extended by Banker et al. [12], is a data analytics approach that can be used for evaluating the relative performances of a group of homogeneous decision-making units (DMUs), which in practice consume multiple inputs to gain multiple outputs. The basic logic behind the DEA methodology is that it compares DMUs' real activity levels relative to the ideal status by projecting their actual input-output bundle onto the production frontier. To obtain the production frontier, all DMUs' observed inputs and outputs are used to construct a production possibility set (PPS) with a set of certain

axiomatic hypothesis, while the production frontier is an envelopment of the production possibility set. The DEA methodology has many apparent characteristics/advantages, and since its inception work in Charnes et al. [11], DEA has been applied to many kinds of activities in various different contexts [13–16]. In addition, the DEA methodology has also proven to be a powerful and preferable method for performance evaluation in the banking industry and has been frequently applied to this industry [2–4, 17].

The conventional DEA methods allow each DMU to generate a set of relative weights to maximize its ratio efficiency of aggregated weighted outputs to aggregated weighted inputs while ensuring that the same ratio is no more than one for all DMUs, and the maximum ratio is considered the performance index for the evaluated DMU [18, 19]. The weight determination is critical to performance evaluation results, but there are some significant concerns that reduce the applicability of DEA-based performance analytics and applications [20, 21]. On the one hand, each DMU selects its most favorable set of weights to maximize its efficiency ratio, and thus, the efficiency score of each DMU might be too optimistic or even impossible due to the unrealistic set of weights. On the other hand, each DMU selects its set of weights separately, and as a result, their performance scores are obtained under different standards and thus are not comparable.

Many studies have been proposed for more reasonable performance analytics by focusing on the selection of feasible weights. Cook et al. [22] and Roll et al. [23] suggest a common set of weights method that attempts to find a common set of weights, and the performance assessment is implemented using that common set of weights. Cook and Kress [24] also address the common set of weights by minimizing the gap of upper and lower bounds of weights. Kao and Hung [25] suggest generating a common set of weights by minimizing the sum of squared difference between the possible efficiency scores for the common set of weights and the CCR efficiency score across all DMUs. Similar studies can also be found in Liu & Peng [26], Kao [27], Zohrehbandian et al. [28], Ramazani-Tarkhorani et al. [29], Shabani et al. [30], Li et al. [31], and Li et al. [32]. Although the common set of weights method can provide a common evaluation standard for all DMUs, its major problem is that it still considers only one possibility for weights upon which the performance is estimated. Moreover, the determination of the common set of weights is still a big problem that will affect the performance analytics results relative to different common sets of weights, and a consensus regarding this has not been reached thus far.

Another research stream focuses on the cross-efficiency method, in which each DMU selects a set of common weights and then the set of common weights is used to evaluate each DMU [33]. It is notable that the classic DEA approach evaluates each DMU's relative efficiency using its favorable set of weights [18, 34], while the cross-efficiency method requires that each DMU's favorable set of weights be used to evaluate itself as well as the other DMUs' relative efficiency. As a result, several sets of weights are used to measure the relative performance, which is a great improvement relative to classic DEA approaches considering only one set of weights. Furthermore, each DMU will have a maximal efficiency score based on self-appraisal and several smaller efficiency scores based on peer appraisal. The ultimate cross-efficiency score can be aggregated with these self-appraisal and peer appraisal scores for each individual DMU [35–41]. The DEA cross-efficiency method has some preferable characteristics, such as satisfied discrimination power between good and poor performances [42], a full ranking of all DMUs [43], and more realistic weights attached to various inputs and outputs [44]. The literature has witnessed numerous studies on various cross-efficiency evaluation approaches for many kinds of real applications [45–47]. Although the cross-efficiency method considers several sets of weights to measure the performance, it is insufficient to involve all performance possibilities. Moreover, the determination of nonunique weights from each DMU's perspective will also reduce the applicability of cross-efficiency methods, as does the aggregation of individual cross-efficiencies [41, 48–50].

The recent research by Salo and Punkka [21] suggests developing ratio-based efficiency analysis over all sets of feasible weights. Salo and Punkka [21] build ranking intervals, dominance relations, and efficiency bounds to show how the DMUs' efficiency ratios relate to each other for all sets of feasible weights rather than for some sets of weights that are typically used in classic DEA studies. More specifically, Tang et al. [51] propose a novel efficiency probability dominance model and develop the dominance efficiency probability over all sets of feasible weights, but their approach is based on a radial model under the constant returns to scale (CRS) assumption, and only traditional desirable outputs are considered by ignoring undesirable outputs. Shi [52] extends the Salo and Punkka [21] model over sets of all feasible weights to a more common and practical case considering the internal two-stage production structure. The proposed approach calculates each DMU's efficiency bounds for the overall system as well as the efficiency bounds for each subsystem. Li et al. [53] build the efficiency ranking interval for two-stage production systems and calculate each DMU's ranking interval for the overall system, as well as for each substage. Li et al. [54] propose a fixed cost allocation approach based on the efficiency ranking concept, which addresses the performance and efficiency ranking interval by considering all relative weights. It is of vital significance to consider all sets of feasible weights because doing so can address all possibilities from a data analytics perspective and provide evaluation results that are more logical and fairer.

In this paper, we will develop a dominance probability approach with undesirable outputs to assess the ratio performance based on DEA models, and the proposed approach is illustrated with Chinese listed banks. From a data-driven analytics perspective, we will consider all sets of feasible weights that are used for estimating the ratio performance. Towards that purpose, we first build a performance evaluation model to address the banking activities in the classic DEA framework by considering only a set of optimal weights. Since banking operations inevitably yield some

undesirable by-products, such as bad debts that are jointly produced with incomes, an extended eco-inefficiency model is developed. Furthermore, the eco-inefficiency model is used to develop the pair dominance structure taking all sets of weights into account based on Tang et al. [51]. The performance dominance probability is proposed to calculate the average probability of a certain DMU's performance dominating all DMUs. A larger performance dominance probability indicates that it is easier for that DMU to dominate all other DMUs, implying that its inefficiency score is more likely to be smaller than that of other DMUs in the sense of data-driven analytics. Finally, the proposed approach is applied to a four-year dataset of 32 Chinese listed banks, and the empirical results show that (1) the inefficiency dominance probability is largely different from inefficiency scores; (2) these state-owned commercial banks are more likely to have a better dominance performance, while local rural commercial banks might have very promising inefficiency performances in some extreme situations but are likely to have poor performance in the sense of inefficiency dominance probability; and (3) China Construction Bank, Industrial and Commercial Bank of China, and Industrial Bank are the top three listed banks based on operations analytics, and on the contrary, Suzhou Rural Commercial Bank, Rural Commercial Bank of Zhangjiagang, and Jiangyin Rural Commercial Bank are the lowest three banks with inefficiency dominance probability. This paper contributes to the literature in at least the following aspects. First, this paper extends a new approach in the DEA framework by taking all sets of feasible weights into account, whereas previous studies have considered only one or several sets of weights. Second, this paper establishes a pairwise performance dominance concept, which can help decision-makers analyze the performance relation in any context with price information (i.e., weights or multipliers). Third, this paper analyzes the performance of Chinese listed banks and provides some empirical findings, which can facilitate the banking industries in China.

The remainder of this paper is organized as follows. Section 2 develops the mathematical methodology of an extended eco-inefficiency model with undesirable outputs and performance dominance structure using inefficiency scores. Afterwards, the proposed approach is used to study the empirical performance analytics of 32 listed banks in Section 3. Finally, Section 4 concludes and summarizes this paper.

2. Mathematical Modeling

We first propose an extended eco-inefficiency model to address banking activities and possible relative performances in Section 2.1. Furthermore, we build a performance dominance structure considering all sets of feasible weights in Section 2.2.

2.1. An Extended Eco-Inefficiency Model. Suppose a set of n peer banks, with each bank using m inputs for the sake of producing s traditional desirable outputs as well as q undesirable outputs, such as bad debt in the illustrative application. A bad debt or nonperforming loan is a jointly produced and unavoidable by-product in the banking industry. Without loss of generality, we consider each bank as a homogeneous decision-making unit (DMU) in the DEA framework. Furthermore, $\mathrm{DMU}_j\,(j = 1, \ldots, n)$ consume inputs $X_j = (x_{1j}, \ldots, x_{mj})$ to produce desirable outputs $Y_j = (y_{1j}, \ldots, y_{sj})$ and undesirable outputs $B_j = (b_{1j}, \ldots, b_{qj})$, respectively. Before constructing the modeling, a core task is to identify appropriate methods to handle undesirable outputs. It is clear that the strong and weak disposability assumption of undesirable outputs and desirable outputs are the two most common and natural methods in the literature [55–57]. A significant feature between the strong and weak disposability assumption is whether undesirable outputs can be produced without damage or subsequent cost to desirable outputs [58]. If undesirable outputs can be freely generated without damage or subsequent cost, implying that both inputs and outputs can change unilaterally without compromising each other, then undesirable outputs are assumed to be strongly disposable. In contrast, if the production of undesirable outputs indeed has some damage or subsequent cost to inputs or desirable outputs, implying that a reduction in undesirable outputs would result in a reduction of desirable outputs simultaneously [59, 60], then undesirable outputs are assumed to be weak disposable. Here, we consider the weak disposability assumption because it is more suitable for the real world and, more specifically, for the empirical application of banking operations, where it is very difficult to freely reduce bad debts without affecting incomes and changing banking operations. To this end, the production possibility set (PPS) under the variable returns to scale (VRS) assumption can be formulated as follows:

$$\mathrm{PPS} = \left\{ \left(x_i, y_r, b_p\right) \left| \begin{array}{ll} \sum_{j=1}^{n} \lambda_j x_{ij} \le x_i, & i = 1, \ldots, m \\ \rho_j \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_r, & r = 1, \ldots, s \\ \rho_j \sum_{j=1}^{n} \lambda_j b_{pj} = b_p, & p = 1, \ldots, q \\ \sum_{j=1}^{n} \lambda_j = 1 & \\ 0 \le \rho_j \le 1, \lambda_j \ge 0, & j = 1, \ldots, n \end{array} \right. \right\}. \tag{1}$$

The above formula is nonlinear since both the reduction factor ρ_j and intensity variable λ_j are unknown. Furthermore, we can equivalently change formula (1) into a linear version, which is presented in the following formula:

$$\mathrm{PPS} = \left\{ \left(x_i, y_r, b_p\right) \left| \begin{array}{ll} \sum_{j=1}^{n} \left(\lambda_j + \eta_j\right) x_{ij} \le x_i, & i = 1, \ldots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_r, & r = 1, \ldots, s \\ \sum_{j=1}^{n} \lambda_j b_{pj} = b_p, & p = 1, \ldots, q \\ \sum_{j=1}^{n} \left(\lambda_j + \eta_j\right) = 1, & \lambda_j, \eta_j \ge 0, j = 1, \ldots, n \end{array} \right. \right\}. \tag{2}$$

Based on formula (2), both desirable and undesirable outputs are weighted by nondisposed intensity variables λ_j, whereas the inputs are weighted by the sum of nondisposed intensity variables λ_j and disposed intensity variables η_j. In addition, the VRS assumption is ensured by summing the total nondisposed intensity variables λ_j and disposed intensity variables η_j to 1, i.e., $\sum_{j=1}^{n}(\lambda_j+\eta_j)=1$.

Based on the above PPS in formula (2), we can build mathematical models to compute the relative performance of DMUs. In this paper, we follow the practice of Chen and Delmas [58] to develop an extended eco-inefficiency model for performance evaluation since the eco-inefficiency model has some advantages in modeling activities with undesirable outputs compared with four well-established models in the literature (undesirable outputs as inputs, transformation of undesirable outputs, directional distance function, and hyperbolic efficiency model. Readers can refer Chen and Delmas [58] for details on the comparison). The extended eco-inefficiency model is formulated as follows:

$$
\begin{aligned}
inE_d^* = \text{Max}\ & \frac{\sum_{i=1}^{m} g_i^x/x_{id} + \sum_{r=1}^{s} g_r^y/y_{rd} + \sum_{p=1}^{q} g_p^b/b_{pd}}{m+s+q} \\
\text{s.t.}\quad & \sum_{j=1}^{n}\left(\lambda_j+\eta_j\right)x_{ij} \le x_{id} - g_i^m, \quad i=1,\ldots,m \\
& \sum_{j=1}^{n}\lambda_j y_{rj} \ge y_{rd} + g_r^y, \quad r=1,\ldots,s \\
& \sum_{j=1}^{n}\lambda_j b_{pj} = b_{pd} - g_p^b, \quad p=1,\ldots,q \\
& \sum_{j=1}^{n}\left(\lambda_j+\eta_j\right) = 1 \\
& \lambda_j, \eta_j, g_i^m, g_r^y, g_p^b \ge 0, \quad j=1,\ldots,n; \\
& \quad r=1,\ldots,s; p=1,\ldots,q.
\end{aligned} \tag{3}
$$

In model (3), the variables g_i^x, g_r^y, and g_p^b represent the amount of potential improvements in inputs, desirable outputs, and undesirable outputs, respectively, that the evaluated DMU can make relative to its current input usage and output production to reach its ideal benchmark target on the efficiency frontier. The potential improvements reflect input reduction potentials and desirable output expansion potentials (or undesirable output reduction potentials) instead of actual input usage and output production [61, 62]. Model (3) uses a slack-based formula that is similar to the directional distance function (DDF) model to maximize the average additive inefficiency index across all input and output measures, where the inefficiency index represents potential improvements divided by observed inputs or outputs. More specifically, the optimal direction vector of model (3) can be endogenously obtained in a similar way as that of Arabi et al. [63]. For that purpose, suppose $g_i^x=\beta\cdot\overline{g}_i$, $g_r^y=\beta\cdot\widetilde{g}_r$, and $g_p^b=\beta\cdot\widehat{g}_p$, where the direction vector is $\mathbf{g}=(\overline{g}_i,\widetilde{g}_r,\widehat{g}_p)$. Solving model (3) determines an optimal solution $(g_i^{x*}, g_r^{y*}, g_p^{b*})$, then we have $\beta=(g_i^{x*}/\overline{g}_i)=(g_r^{y*}/\widetilde{g}_r)=(g_p^{b*}/\widehat{g}_p)(i=1,\ldots,m;\ r=1,\ldots,s;\ p=1,\ldots,q)$. Hence, we have a system of $(m+s+q+1)$ unknown variables $(\beta,\overline{g}_i,\widetilde{g}_r,\widehat{g}_p)$ and $(m+s+q)$ linearly independent equations $g_1^{x*}\overline{g}_2=g_2^{x*}\overline{g}_1,\ldots,g_m^{x*}\overline{g}_1=g_1^{y*}\overline{g}_m$, $g_1^{y*}\widetilde{g}_2=g_2^{y*}\widetilde{g}_1,\ldots,g_s^{y*}\widehat{g}_1=g_1^{b*}\widetilde{g}_s$, $g_1^{b*}\widehat{g}_2=g_2^{b*}\widehat{g}_1,\ldots,g_{q-1}^{b*}\widehat{g}_q=g_q^{b*}\widehat{g}_{q-1}$, and $g_q^{b*}=\beta\cdot g_q$. Together with another equation such as $\sum_{i=1}^{m}\overline{g}_i+\sum_{r=1}^{s}\widetilde{g}_r+\sum_{p=1}^{q}\widehat{g}_p=1$ that is used to ensure a bounded and closed space, we then have a system of $(m+s+q+1)$ unknown variables and $(m+s+q+1)$ linearly independent equations. Therefore, this system has a unique solution and we can obtain a unique optimal direction.

Model (3) is slightly different from that of Chen and Delmas [58] in several aspects: first, we also take the input improvement into account, while Chen and Delmas [58] studied only the output improvement; secondly, we assume the weak disposability assumption of desirable outputs and undesirable outputs, while the strong disposability assumption was modeled in Chen and Delmas [58]. In addition, the VRS assumption is considered in model (3) such that it is more suitable for real applications. Since the individual inefficiency index theoretically has a value ranging from zero to unity for inputs and undesirable outputs and a value from zero to infinity for desirable outputs, the overall average inefficiency of DMU_d also takes a value from zero to infinity. The larger the average inefficiency index is, the more inefficient the evaluated DMU is. An average inefficiency index of zero value means that the considered DMU is on the efficiency frontier and has no slack for improvement, and hence, the DMU is efficient.

Furthermore, model (4) is a dual formulation of the above model (3) in its multiplier formulation:

$$
\begin{aligned}
inE_d^* = \text{Min}\quad & \sum_{i=1}^{m} v_i x_{id} - \sum_{r=1}^{s} u_r y_{rd} + \sum_{p=1}^{q} w_p b_{pd} + u_0 \\
\text{s.t.}\quad & \sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} + \sum_{p=1}^{q} w_p b_{pj} + u_0 \ge 0, \\
& \quad j=1,\ldots,n \\
& \sum_{i=1}^{m} v_i x_{ij} + u_0 \ge 0, \quad j=1,\ldots,n \\
& v_i \ge 1/(m+s+q)x_{id}, \quad i=1,\ldots,m \\
& u_r \ge 1/(m+s+q)y_{rd}, \quad r=1,\ldots,s \\
& w_p \ge 1/(m+s+q)b_{pd}, \quad p=1,\ldots,q \\
& v_i, u_r \ge 0, i=1,\ldots,m; r=1,\ldots,s; \\
& \quad w_p, u_0 \text{ are free}, p=1,\ldots,q.
\end{aligned} \tag{4}
$$

Model (4) computes the inefficient component (i.e., the difference between aggregated inputs and aggregated outputs) for the evaluated DMU, yet the inefficient component is nonnegative for all DMUs, and some constraints on

multipliers are held. Solving model (4) for each DMU_d ($d = 1, \ldots, n$) determines a series of inefficiency scores inE_d^* using a series of optimal solutions $(u_r^{d*}, v_i^{d*}, w_p^{d*}, u_0^{d*})$. The inefficiency score can be used for a performance indicator among all DMUs, and the smaller the inefficiency score is, the better the performance of DMU_d is.

2.2. Dominance Probability Based on Inefficiency Scores. It is notable that the inefficiency score inE_d^* obtained previously can be used to analyze the performance of Chinese listed banks, but there are two main concerns. On the one hand, it is calculated by only considering the optimal weight plan $(u_r^{d*}, v_i^{d*}, w_p^{d*}, u_0^{d*})$ while ignoring any other feasible weights, and thus, the obtained inefficiency score inE_d^* might be too extreme or even unrealistic. On the other hand, the inefficiency score inE_d^* is calculated separately for each DMU_d ($d = 1, \ldots, n$), and different weights will be preferred by different DMUs; thus, the results are not completely comparable.

Since the resulting inefficiency indexes can change relative to different sets of weights, it is important to explore the performance associated with all sets of feasible input/output weights. To this end, we focus on the efficiency dominance concept of Salo and Punkka [21]. As well defined and discussed in Salo and Punkka [21] and Tang et al. [51], the dominance relation is determined through a pairwise efficiency comparison among DMUs. Furthermore, a certain DMU dominates another DMU if and only if its efficiency score is as large as that of the other for all sets of feasible input/output weights and is larger for at least some sets of feasible input/output weights. Here, we follow the same idea of Salo and Punkka [21] and Tang et al. [51] to determine the dominance relation of Chinese listed banks. For comparison, we take inevitable undesirable outputs in banking operations, such as bad debts, into account. Furthermore, we follow Chen and Delmas [58] in focusing on eco-inefficiency scores rather than efficiency scores through a nonradial directional distance function model. To this end, we first build the inefficiency dominance concept as follows.

Definition 1. DMU_d dominates DMU_k (denoted as $\mathrm{DMU}_d \succ \mathrm{DMU}_k$) if and only if DMU_d always has a smaller inefficiency score relative to DMU_k for all sets of feasible input and output weights.

The dominance relation based on inefficiency scores is determined if the inefficiency score for a certain DMU_d is as small as that of DMU_k for all sets of feasible input/output weights and is smaller for at least some sets of feasible input/output weights. The dominance relation between DMU_d and DMU_k is determined through their inefficiency comparison. By rethinking the idea of model (3) and model (4), which calculate the maximal inefficiency score, we can formulate model (5) to calculate the inefficiency range of DMU_d when DMU_k is fixed with a prespecified inefficiency level of zero by requiring the constraint that $inE_k = \sum_{i=1}^m v_i x_{ik} - \sum_{r=1}^s u_r y_{rk} + \sum_{p=1}^q w_p b_{pk} + u_0 = 0$. In fact, the inefficiency level of DMU_k can be set to any nonnegative value M, and by substituting u_0 with $u_0 - M$, we can get the same dominance probability as given in Definition 2 and Definition 3; hence, we immediately set the inefficiency level of DMU_k to zero for simplification in the following model:

$$
\begin{aligned}
\frac{inE_{\widetilde{d}k}^{\max}}{inE_{\widetilde{d}k}^{\min}} = \quad & \frac{\mathrm{Min}}{\mathrm{Max}} \sum_{i=1}^m v_i x_{id} - \sum_{r=1}^s u_r y_{rd} + \sum_{p=1}^q w_p b_{pd} + u_0 \\
\text{s.t} \quad & \sum_{i=1}^m v_i + \sum_{r=1}^s u_r + \sum_{p=1}^q w_p = 1 \\
& \sum_{i=1}^m v_i x_{ik} - \sum_{r=1}^s u_r y_{rk} + \sum_{p=1}^q w_p b_{pk} + u_0 = 0 \\
& \sum_{i=1}^m v_i x_{ij} + u_0 \geq 0, \quad j = d, k \\
& v_i \geq \frac{1}{(m+s+q)x_{id}}, \quad i = 1, \ldots, m \\
& u_r \geq \frac{1}{(m+s+q)y_{rd}}, \quad r = 1, \ldots, s \\
& w_p \geq \frac{1}{(m+s+q)b_{pd}}, \quad p = 1, \ldots, q \\
& v_i, u_r \geq 0, i = 1, \ldots, m; r = 1, \ldots, s; \\
& w_p, u_0 \text{ are free}, p = 1, \ldots, q.
\end{aligned}
\tag{5}
$$

An additional constraint that $\sum_{i=1}^m v_i + \sum_{r=1}^s u_r + \sum_{p=1}^q w_p = 1$ is inserted into model (5) to make the feasible weight space closed and bounded. The optimal objective function for model (5) shows the lower and upper bounds on how much different $\mathrm{DMU_d}$'s inefficiency score can be relative to DMU_k across all sets of feasible input/output weights. Using model (5), the dominance structure can be determined for any pairwise DMUs. More specifically, if the inefficiency level of DMU_k is fixed to zero and if $inE_{\widetilde{d}k}^{\max} < 0$, which means that DMU_d will always have a smaller inefficiency score compared with DMU_k, then DMU_d dominates DMU_k. In contrast, if $inE_{\widetilde{d}k}^{\min} > 0$, which means that DMU_d will always have a larger inefficiency score than DMU_k (which has an inefficiency level of zero), then DMU_d is dominated by DMU_k. For more general cases, however, we cannot obtain the complete dominance relation, which is usually true in practice. Therefore, we propose determining the performance dominance probability. To this end, we follow the work of Tang et al. [51] in building the inefficiency dominance probability concept, as given in Definition 2.

Definition 2. When DMU_k has an inefficiency score of inE_k, the probability that DMU_d dominates DMU_k over all sets of feasible input and output weights is calculated by $P_{\widetilde{d}>k} = (inE_k - inE_{\widetilde{d}k}^{\min} / inE_{\widetilde{d}k}^{\max} - inE_{\widetilde{d}k}^{\min})$.

It is clear that, if $inE_k \leq inE_{\widetilde{d}k}^{\min}$, which means that DMU_d will always have a larger inefficiency by remaining the inefficiency inE_k for DMU_k, the inefficiency dominance

probability of DMU_d relative to DMU_k would take a nonpositive value. That is, it is impossible for DMU_d to dominate DMU_k. For the sake of a bounded range, we assume that $P_{\widetilde{d}>k} = 0$ if $inE_k \le inE_{\widetilde{d}k}^{\min}$. For a more general case in which $inE_{\widetilde{d}k}^{\min} \le inE_k \le inE_{\widetilde{d}k}^{\max}$, the probability that DMU_d dominates DMU_k takes a value from zero to unity. A larger value of $P_{\widetilde{d}>k}$ means that it is more likely for DMU_d to have a smaller inefficiency score compared with DMU_k over all sets of feasible input/output weights.

Note in addition that Definition 2 fixes the inefficiency level of DMU_k to calculate the inefficiency range of DMU_d and further computes the inefficiency dominance probability of DMU_d relative to DMU_k. In contrast, we can also compute the inefficiency dominance probability of DMU_d relative to DMU_k by fixing the inefficiency level of DMU_d and calculating the inefficiency range of DMU_k. The above idea is formulated in model (6), which is very similar to model (5) but substitutes DMU_k for DMU_d:

$$\begin{aligned}
\frac{inE_{\widetilde{k}d}^{\max}}{inE_{\widetilde{k}d}^{\min}} = \quad & \frac{\text{Min}}{\text{Max}} \sum_{i=1}^{m} v_i x_{ik} - \sum_{r=1}^{s} u_r y_{rk} + \sum_{p=1}^{q} w_p b_{pk} + u_0 \\
\text{s.t.} \quad & \sum_{i=1}^{m} v_i + \sum_{r=1}^{s} u_r + \sum_{p=1}^{q} w_p = 1 \\
& \sum_{i=1}^{m} v_i x_{id} - \sum_{r=1}^{s} u_r y_{rd} + \sum_{p=1}^{q} w_p b_{pd} + u_0 = 0 \\
& \sum_{i=1}^{m} v_i x_{ij} + u_0 \ge 0, \quad j = d, k \\
& v_i \ge \frac{1}{(m+s+q)x_{ik}}, \quad i = 1, \ldots, m \\
& u_r \ge \frac{1}{(m+s+q)y_{rk}}, \quad r = 1, \ldots, s \\
& w_p \ge \frac{1}{(m+s+q)b_{pk}}, \quad p = 1, \ldots, q \\
& v_i, u_r \ge 0, i = 1, \ldots, m; r = 1, \ldots, s; \\
& w_p, u_0 \text{ are free}, p = 1, \ldots, q.
\end{aligned} \tag{6}$$

An alternative inefficiency dominance probability of DMU_d relative to DMU_k by fixing the inefficiency level of DMU_d is given in Definition 3.

Definition 3. When DMU_d has an inefficiency score of inE_d, the probability that DMU_d dominates DMU_k over all sets of feasible input and output weights is calculated by $P_{d>\widetilde{k}} = (inE_{\widetilde{k}d}^{\max} - inE_d / inE_{\widetilde{k}d}^{\max} - inE_{\widetilde{k}d}^{\min})$.

Furthermore, the overall probability that the inefficiency score of DMU_d dominates that of DMU_k is the average of the two probabilities by fixing the inefficiency level of DMU_d and DMU_k. More specifically, Definition 4 gives the pairwise performance dominance probability with regard to inefficiency scores.

Definition 4. The pairwise performance dominance probability of DMU_d relative to DMU_k over all sets of feasible input and output weights is $P_{d>k} = ((P_{\widetilde{d}>k} + P_{d>\widetilde{k}})/2)$.

The classic DEA methods allow each DMU to generate a set of relative weights to maximize its ratio of aggregated weighted outputs to aggregated weighted inputs while ensuring that the same ratio is no more than one for all DMUs, and the maximum ratio is considered the efficiency score for the evaluated DMU. By taking all sets of feasible weights and the inefficiency dominance structure into account, the overall inefficiency dominance probability for a certain DMU_d among all DMUs can be calculated by the average of pair inefficiency dominance probabilities across all DMUs. The above idea is given in Definition 5.

Definition 5. The performance dominance probability of DMU_d across all DMUs over all sets of feasible input and output weights is $P_d = \sum_{k=1}^{n} P_{d>k}/n$.

The classic DEA approaches use deterministic (in)efficiency scores to measure the relative performance, while the performance dominance probability is an alternative performance indicator from a data analytics perspective that considers all sets of feasible weights that are stochastic to determine the relative performance. It is rather remarkable that different sets of weights will cause different performance measures, and the performance dominance probability involves all possibilities over all sets of feasible input and output weights. The performance dominance probability of DMU_d calculates the probability of its performance dominating the set of all DMUs. A larger performance dominance probability indicates that it is much easier for that DMU to dominate other DMUs, implying that its inefficiency score is more likely to be smaller than that of other DMUs.

3. Illustrative Application of Chinese Listed Banks

In this section, we illustrate the proposed approach using empirical performance analytics for 32 Chinese listed banks. Since the proposed approach considers all sets of feasible weights, the performance relations and ratio index results are more comprehensive and reasonable.

3.1. Data Description. This section addresses the performance of listed banks in China. For simplification and research purposes, we consider only those banks that have been registered in China and that are listed in the mainland of China. More specifically, only banks that are owned by Chinese organizations and are listed on the Shenzhen Stock Exchange and Shanghai Stock Exchange are collected. In contrast, neither Chinese banks listed on other stock exchanges nor foreign banks listed on the Shenzhen Stock Exchange and Shanghai Stock Exchange are involved in this study. As a result, we have 32 listed banks. For the research

purpose, we give these 32 banks and their corresponding codes in Table 1.

In practice, each bank will consume multiple inputs to generate multiple outputs and more specifically mainly for profits. In this study, we follow similar studies such as Wang et al. [4], Zha et al. [1], Fukuyama and Matousek [64], Li et al. [65], and Zhu et al. [2] in taking employment referring to human resource investment and manpower, fixed asset referring to the asset value of physical capital that can be used for business activities, and operation cost as three inputs. Note in addition that the operation cost in this study excludes the expense of labor input that occurs in banking operations because the employment has already taken the labor input into account. Furthermore, we consider three different outputs generated in banking operations, with interest income and noninterest income being two desirable outputs and nonperforming bad loan percentage in the current year as an undesirable output. The interest income is derived directly from the gap between the interest paid on deposits and the interest earned from loans, while the noninterest income is primarily derived from commissions, securities investments, fees, and other business activity incomes. However, a bad loan is a jointly produced and unavoidable by-product that will greatly harm the bank. The inputs and outputs to be used in this study are summarized in Table 2.

Our empirical study contains operation data for 32 Chinese listed banks over the 2014–2018 period, accounting for 160 observations. All data for these listed banks were collected from official sources of bank annual reports and the financial reports of banks in China Stock Market Accounting Research (CSMAR) during 2014–2018. Table 3 shows the descriptive statistics of the inputs, desirable outputs, and undesirable outputs of these 160 observations. It can be found that both the average fixed asset and operation cost among the 32 listed banks are increasing year by year, but the average employment and bad debt percentage increased to a peak in 2016 and then decreased continuously. Furthermore, both interest income and noninterest income show an increasing trend but decreased in a year.

3.2. Result Analysis. To provide data analytics of bank performance, we first calculate the inefficiency scores using model (3) or model (4) in the nonradial DDF-based formulation under the VRS property. The inefficiencies of these 32 banks from 2014 to 2018 are given in Table 4. Since the inefficiency score represents potential improvements divided by the observed inputs or outputs, an inefficiency score of zero indicates that there will be no improvement potential. Table 4 shows that, by selecting the optimal set of weights to aggregate inputs and outputs, many listed banks will be extremely efficient without improvement potentials. There are always ten banks that have an inefficiency score larger than zero, but the average inefficiency score across these 32 listed banks fluctuates according to the year. Since the VRS analysis is adopted in this study, we may not draw any significant conclusion as to inefficiency changes year by year. Furthermore, some banks (DMU_6, Bank of Guiyang; DMU_8, Huaxia Bank; DMU_{15}, Bank of Ningbo; and DMU_{32}, Zijin Rural Commercial Bank) will always have a nonzero inefficiency, meaning that these banks always show very terrible performance compared with banks that have a zero-value inefficiency index.

Table 1: Codes for 32 Chinese listed banks.

DMUs	Banks	Abbreviation
DMU_1	Bank of Beijing	BOB
DMU_2	Changshu Rural Commercial Bank	CRCB
DMU_3	Bank of Chengdu	BCD
DMU_4	Industrial and Commercial Bank of China	ICBC
DMU_5	China Everbright Bank	CEB
DMU_6	Bank of Guiyang	BOG
DMU_7	Bank of Hangzhou	BOH
DMU_8	Huaxia Bank	HB
DMU_9	China Construction Bank	CCB
DMU_{10}	Bank of Jiangsu	BOJ
DMU_{11}	Jiangyin Rural Commercial Bank	JRCB
DMU_{12}	Bank of Communications	BC
DMU_{13}	China Minsheng Bank	CMSB
DMU_{14}	Bank of Nanjing	BON
DMU_{15}	Bank of Ningbo	BN
DMU_{16}	Agricultural Bank of China	ABC
DMU_{17}	Ping An Bank	PB
DMU_{18}	Shanghai Pudong Development Bank	SPDB
DMU_{19}	Bank of Qingdao	BOQ
DMU_{20}	Qingdao Rural Commercial Bank	QRCB
DMU_{21}	Bank of Shanghai	BOS
DMU_{22}	Suzhou Rural Commercial Bank	SRCB
DMU_{23}	Wuxi Rural Commercial Bank	WRCB
DMU_{24}	Bank of Xian	BOX
DMU_{25}	Industrial Bank	IB
DMU_{26}	Rural Commercial Bank of Zhangjiagang	RCBZ
DMU_{27}	Bank of Changsha	BCS
DMU_{28}	China Merchants Bank	CMB
DMU_{29}	Bank of Zhengzhou	BOZ
DMU_{30}	Bank of China	BOC
DMU_{31}	China CITIC Bank	CCB
DMU_{32}	Zijin Rural Commercial Bank	ZRCB

Table 2: Input and output variables.

Input/output	Variable	Notation	Unit
Inputs	Employment	x_1	Person count
	Fixed assets	x_2	Million yuan
	Operation costs	x_3	Million yuan
Desirable outputs	Interest income	y_1	Million yuan
	Noninterest income	y_2	Million yuan
Undesirable outputs	Bad debt percentage	z_1	Percentage

Since the previous inefficiency scores are separately derived by considering only one optimal set of weights, the resulting performance information might be unrealistic and unreasonable. Therefore, we can use the proposed eco-inefficiency dominance probability approach in this paper to analyze the banking performance considering all sets of feasible weights. To this end, we first use model (5) to

Table 3: Descriptive statistics for input-output measures.

Year	Statistics	x_1	x_2	x_3	y_1	y_2	z_1
2014	Max	493583	196238	271132	849879	165370	2.7100
	Min	1089	412.01	1151.41	3533.90	109.48	0.7500
	Mean	67582	28499.15	48231.62	154112.69	25685.99	1.2531
	SD	135316	55898.04	78151.35	235785.69	44163.22	0.4237
2015	Max	503082	221502	306395	871779	189780	2.3900
	Min	1180	418.04	1245.26	3486.11	130.69	0.8300
	Mean	69772	31335.97	57387.23	162109.41	30344.05	1.5308
	SD	136444	60262.26	87459.17	243294.78	49419.92	0.4226
2016	Max	496698	243619	282712	791480	204045	2.4100
	Min	1352	413.99	1235.88	3268.89	162.62	0.8700
	Mean	70266	34778.86	58285.96	151790.21	35560.52	1.6013
	SD	134489	65118.10	85168.72	220693.57	57189.80	0.3678
2017	Max	487307	245687	331518	861594	204424	2.3900
	Min	1426	462.93	1260.89	3789.14	166.05	0.8200
	Mean	69782	36383.26	60079.96	166927.92	35168.24	1.5431
	SD	132071	66621.76	91681.04	239463.71	53045.31	0.3240
2018	Max	473691	253525	368966	948094	201271	2.4700
	Min	1454	418.08	1733.55	4567.00	203.17	0.7800
	Mean	69354	38380.34	67444.02	183050.26	39183.08	1.5034
	SD	129697	70061.74	100964.72	261751.20	55000.40	0.3382

Table 4: Inefficiency scores of 32 listed banks from 2014 to 2018.

Banks	2014	2015	2016	2017	2018
DMU_1	0.0000	0.0000	0.0000	0.0000	0.0000
DMU_2	0.0000	0.3483	0.6442	0.5430	0.3483
DMU_3	0.0000	0.0979	0.2730	0.0000	0.0979
DMU_4	0.0000	0.0000	0.0000	0.0000	0.0000
DMU_5	0.0000	0.0590	0.0000	0.1087	0.0590
DMU_6	0.2345	0.3469	0.3273	0.5898	0.3469
DMU_7	0.1798	0.0000	0.0000	0.0000	0.0000
DMU_8	0.2880	0.3059	0.2288	0.2768	0.3059
DMU_9	0.0000	0.0000	0.0000	0.0000	0.0000
DMU_{10}	0.0000	0.0000	0.0000	0.0000	0.0000
DMU_{11}	0.0000	0.0000	0.0000	0.0000	0.0000
DMU_{12}	0.1449	0.0000	0.0000	0.0000	0.0000
DMU_{13}	0.0000	0.0000	0.0000	0.0000	0.0000
DMU_{14}	0.2088	0.1072	0.1415	0.0000	0.1072
DMU_{15}	0.2793	0.2415	0.2018	0.2225	0.2415
DMU_{16}	0.1926	0.0000	0.0000	0.0000	0.0000
DMU_{17}	0.0000	0.0000	0.0000	0.0000	0.0000
DMU_{18}	0.0567	0.0000	0.0000	0.0000	0.0000
DMU_{19}	0.0000	0.0000	0.0827	0.0000	0.0000
DMU_{20}	0.0000	0.0000	0.0000	0.0000	0.0000
DMU_{21}	0.0000	0.0000	0.0000	0.0000	0.0000
DMU_{22}	0.0000	0.0000	0.0000	0.2032	0.0000
DMU_{23}	0.0000	0.0000	0.0000	0.0000	0.0000
DMU_{24}	0.0000	0.0000	0.0000	0.0000	0.0000
DMU_{25}	0.0000	0.0000	0.0000	0.0000	0.0000
DMU_{26}	0.0000	0.0000	0.0000	0.0000	0.0000
DMU_{27}	0.0000	0.2287	0.2670	0.6379	0.2287
DMU_{28}	0.0000	0.0000	0.0000	0.0000	0.0000
DMU_{29}	0.0000	0.0000	0.1373	0.0967	0.0000
DMU_{30}	0.0000	0.0000	0.0000	0.0000	0.0000
DMU_{31}	0.0634	0.0799	0.0000	0.0000	0.0799
DMU_{32}	0.5982	0.2792	0.3526	0.5700	0.2792
Mean	0.0702	0.0655	0.0830	0.1015	0.0655

calculate the inefficiency score intervals and then use Definition 2 to calculate the first-level pairwise dominating probability in 2018. Since the pairwise dominating probability involves an $n \times n$ matrix that is hard to present in this paper, we arbitrarily take the Bank of Jiangsu (BOJ), Agricultural Bank of China (ABC), and Rural Commercial Bank of Zhangjiagang (RCBZ) for instance, and the first-level inefficiency dominating probability for these three banks across all 32 banks is listed in the second, third, and fourth columns of Table 5, namely, $P_{\widetilde{\mathrm{BOJ}>k}}$, $P_{\widetilde{\mathrm{ABC}>k}}$, and $P_{\widetilde{\mathrm{RCBZ}>k}}$ (it is also possible to consider any other banks as examples to show the calculation results). The results represent the probability of the considered bank having a smaller inefficiency index across any other bank, with different sets of weights being attached to inputs and outputs to ensure an efficient status for other banks. For example, the value of 0.2699 implies that, by fixing the inefficiency score of the Bank of Beijing (DMU_1) to zero, the inefficiency score of the Bank of Jiangsu will be smaller with a probability of 0.2699 and larger with a probability of 0.7301 (1–0.2699). At the same time, we can use model (6) and Definition 3 to calculate another dominating probability, and the second-level results of Bank of Jiangsu (BOJ), Agricultural Bank of China (ABC), and Rural Commercial Bank of Zhangjiagang (RCBZ) in 2018 are given in the last three columns of Table 5.

Without loss of generality, each DMU will always dominate itself, as these three banks will have a dominating probability of 1 to itself regardless of whether the first-level dominance probability or the second-level dominance probability is considered. From Table 5, we can find that all three banks have a larger second-level dominance probability than the first-level dominance probability to other banks, and it is indeed also held for all banks. This difference is due to the definition style of pairwise dominances, and we cannot arbitrarily use one dominating probability to represent the performance assessment with the other being ignored. By averaging the two pairwise dominating probabilities, we can calculate the pairwise dominance probability as well as the dominated probability. Reconsidering the three banks in Table 5, we show the pairwise dominance probability as well as dominated probability for Bank of Jiangsu, Agricultural Bank of China, and Rural Commercial Bank of Zhangjiagang in Table 6. Taking the inefficiency dominance probability of Bank of Jiangsu to Bank of Beijing (DMU_1), for example, the arithmetic mean of 0.2699 and 0.3515 by Definition 4 is exactly the pairwise inefficiency dominance probability of Bank of Jiangsu to Bank of Beijing, 0.3107. Since the pairwise dominance probability shows the probability of the inefficiency score of Bank of Jiangsu relative to any other banks, by considering all sets of feasible input and output weights, it means that the inefficiency score of Bank of Jiangsu is smaller than that of Bank of Beijing with a probability of 0.3107. In contrast, the inefficiency of Bank of Jiangsu will be dominated by Bank of Beijing with a probability of 0.6893.

Furthermore, by aggregating the pairwise inefficiency dominance probability across all banks, we can obtain the average performance dominance probability in terms of inefficiency scores for these three banks, as given in the last column of Table 6. Furthermore, proceeding in the same manner as above, we can determine the inefficiency dominance probability for all 32 Chinese listed banks from 2014 to 2018, as shown in Table 7.

Table 5: Two kinds of dominating probabilities for BOJ, ABC, and RCBZ in 2018.

Banks	Definition 2			Definition 3		
	BOJ	ABC	RCBZ	BOJ	ABC	RCBZ
DMU_1	0.2699	0.5964	0.0093	0.3515	0.9452	0.2111
DMU_2	0.8578	0.6238	0.2563	0.9850	0.9959	0.4689
DMU_3	0.8520	0.6207	0.0496	0.9662	0.9910	0.1966
DMU_4	0.0288	0.3164	0.0016	0.3339	0.3822	0.3216
DMU_5	0.1671	0.5897	0.0074	0.3446	0.9119	0.2663
DMU_6	0.8592	0.6197	0.0386	0.9599	0.9887	0.1905
DMU_7	0.8518	0.6159	0.0253	0.9337	0.9821	0.1961
DMU_8	0.3056	0.6073	0.0106	0.4337	0.9419	0.2603
DMU_9	0.0315	0.1127	0.0017	0.3121	0.1311	0.2989
DMU_{10}	**1.0000**	**0.6052**	**0.0088**	**1.0000**	**0.9589**	**0.1523**
DMU_{11}	0.8514	0.6230	0.3883	0.9915	0.9977	0.4059
DMU_{12}	0.0835	0.5315	0.0042	0.3563	0.7917	0.3073
DMU_{13}	0.1096	0.5695	0.0054	0.3154	0.8709	0.2684
DMU_{14}	0.8678	0.6123	0.0146	0.9135	0.9736	0.1657
DMU_{15}	0.9666	0.6173	0.0286	0.9704	0.9791	0.2599
DMU_{16}	**0.0411**	**1.0000**	**0.0023**	**0.3948**	**1.0000**	**0.3768**
DMU_{17}	0.2062	0.5856	0.0089	0.4109	0.9140	0.3081
DMU_{18}	0.0921	0.5531	0.0046	0.3014	0.8476	0.2634
DMU_{19}	0.8593	0.6219	0.0995	0.9780	0.9943	0.2510
DMU_{20}	0.8454	0.6226	0.1170	0.9772	0.9942	0.2986
DMU_{21}	0.5626	0.6048	0.0133	0.5695	0.9618	0.2139
DMU_{22}	0.8492	0.6230	0.2009	0.9916	0.9978	0.2256
DMU_{23}	0.8463	0.6225	0.1454	0.9886	0.9971	0.1876
DMU_{24}	0.8473	0.6222	0.0825	0.9808	0.9951	0.1796
DMU_{25}	0.0724	0.5560	0.0038	0.2395	0.8469	0.2161
DMU_{26}	**0.8477**	**0.6232**	**1.0000**	**0.9912**	**0.9977**	**1.0000**
DMU_{27}	0.8790	0.6204	0.0512	0.9669	0.9892	0.2431
DMU_{28}	0.1159	0.5628	0.0058	0.3840	0.8491	0.3310
DMU_{29}	0.8588	0.6202	0.0662	0.9644	0.9908	0.2669
DMU_{30}	0.0389	0.3718	0.0021	0.3274	0.4493	0.3107
DMU_{31}	0.1246	0.5690	0.0060	0.3564	0.8716	0.2997
DMU_{32}	0.8494	0.6222	0.1199	0.9848	0.9960	0.2093

As Table 7 shows, these banks have very different inefficiency dominance probabilities over all sets of feasible weights relative to the inefficiency scores derived from only an optimal set of weights. For example, Huaxia Bank (DMU_8) always has a positive inefficiency in each year, and that bank will be ranked after most banks. However, Huaxia Bank will have an inefficiency dominance probability of 0.6105, 0.5885, 0.5749, 0.5640, and 0.5857 in the 2014–2018 period, respectively. This phenomenon implies that Huaxia Bank is more likely to have an inefficiency index smaller than that of half of all banks. In contrast, by considering only the optimal set of weights, the Rural Commercial Bank of Zhangjiagang (DMU_{26}) is extremely efficient with an inefficiency score of zero for all years, but it has a relatively small inefficiency dominance probability in each year (0.2405, 0.2264, 0.2289, 0.2039, and 0.1864, respectively), implying that the performance of Rural Commercial Bank of Zhangjiagang in the sense of inefficiency scores is at a disadvantage to other banks by addressing all weight possibilities.

Table 6: Pairwise dominance probability for BOJ, ABC, and RCBZ in 2018.

Banks	Dominating			Dominated		
	BOJ	ABC	RCBZ	BOJ	ABC	RCBZ
DMU_1	0.3107	0.7708	0.1102	0.6893	0.2292	0.8898
DMU_2	0.9214	0.8098	0.3626	0.0786	0.1902	0.6374
DMU_3	0.9091	0.8058	0.1231	0.0909	0.1942	0.8769
DMU_4	0.1813	0.3493	0.1616	0.8187	0.6507	0.8384
DMU_5	0.2559	0.7508	0.1369	0.7441	0.2492	0.8631
DMU_6	0.9096	0.8042	0.1145	0.0904	0.1958	0.8855
DMU_7	0.8928	0.7990	0.1107	0.1072	0.2010	0.8893
DMU_8	0.3696	0.7746	0.1354	0.6304	0.2254	0.8646
DMU_9	0.1718	0.1219	0.1503	0.8282	0.8781	0.8497
DMU_{10}	**1.0000**	**0.7820**	**0.0805**	**1.0000**	**0.2180**	**0.9195**
DMU_{11}	0.9214	0.8104	0.3971	0.0786	0.1896	0.6029
DMU_{12}	0.2199	0.6616	0.1557	0.7801	0.3384	0.8443
DMU_{13}	0.2125	0.7202	0.1369	0.7875	0.2798	0.8631
DMU_{14}	0.8906	0.7929	0.0902	0.1094	0.2071	0.9098
DMU_{15}	0.9685	0.7982	0.1442	0.0315	0.2018	0.8558
DMU_{16}	**0.2180**	**1.0000**	**0.1895**	**0.7820**	**1.0000**	**0.8105**
DMU_{17}	0.3086	0.7498	0.1585	0.6914	0.2502	0.8415
DMU_{18}	0.1968	0.7004	0.1340	0.8032	0.2996	0.8660
DMU_{19}	0.9187	0.8081	0.1752	0.0813	0.1919	0.8248
DMU_{20}	0.9113	0.8084	0.2078	0.0887	0.1916	0.7922
DMU_{21}	0.5661	0.7833	0.1136	0.4339	0.2167	0.8864
DMU_{22}	0.9204	0.8104	0.2132	0.0796	0.1896	0.7868
DMU_{23}	0.9174	0.8098	0.1665	0.0826	0.1902	0.8335
DMU_{24}	0.9141	0.8086	0.1311	0.0859	0.1914	0.8689
DMU_{25}	0.1559	0.7014	0.1099	0.8441	0.2986	0.8901
DMU_{26}	**0.9195**	**0.8105**	**1.0000**	**0.0805**	**0.1895**	**1.0000**
DMU_{27}	0.9229	0.8048	0.1472	0.0771	0.1952	0.8528
DMU_{28}	0.2499	0.7060	0.1684	0.7501	0.2940	0.8316
DMU_{29}	0.9116	0.8055	0.1666	0.0884	0.1945	0.8334
DMU_{30}	0.1832	0.4106	0.1564	0.8168	0.5894	0.8436
DMU_{31}	0.2405	0.7203	0.1529	0.7595	0.2797	0.8471
DMU_{32}	0.9171	0.8091	0.1646	0.0829	0.1909	0.8354
Mean	0.6096	0.7375	0.1864	0.4217	0.2938	0.8448

Table 7: Inefficiency dominance probability of 32 listed banks from 2014 to 2018.

Banks	2014	2015	2016	2017	2018	Mean
DMU_1	0.6175	0.6149	0.6142	0.6173	0.6235	0.6175
DMU_2	0.2872	0.2633	0.2243	0.2184	0.2293	0.2445
DMU_3	0.4257	0.4131	0.3831	0.3685	0.3971	0.3975
DMU_4	0.7964	0.7936	0.7786	0.7920	0.8056	0.7932
DMU_5	0.6770	0.6678	0.6790	0.6815	0.6411	0.6693
DMU_6	0.3007	0.3382	0.3529	0.3928	0.4268	0.3623
DMU_7	0.4582	0.4853	0.4794	0.4922	0.4908	0.4812
DMU_8	0.6105	0.5885	0.5749	0.5640	0.5857	0.5847
DMU_9	0.8039	0.8091	0.7945	0.8038	0.8132	0.8049
DMU_{10}	**0.5439**	**0.5812**	**0.5893**	**0.6105**	**0.6096**	**0.5869**
DMU_{11}	0.2742	0.2571	0.2469	0.2246	0.2099	0.2425
DMU_{12}	0.7623	0.7480	0.7216	0.7106	0.7032	0.7291
DMU_{13}	0.7042	0.6892	0.6916	0.7231	0.6982	0.7013
DMU_{14}	0.5130	0.5143	0.5269	0.5392	0.5413	0.5269
DMU_{15}	0.4937	0.4849	0.4806	0.4678	0.4710	0.4796
DMU_{16}	**0.7135**	**0.7209**	**0.7130**	**0.7232**	**0.7375**	**0.7216**
DMU_{17}	0.6272	0.6105	0.5922	0.6169	0.6155	0.6125
DMU_{18}	0.7315	0.7255	0.7244	0.7324	0.7331	0.7294
DMU_{19}	0.3614	0.3654	0.3772	0.3510	0.3212	0.3552
DMU_{20}	0.2796	0.2947	0.3033	0.2929	0.3048	0.2951
DMU_{21}	0.5859	0.5885	0.6007	0.5769	0.5712	0.5846
DMU_{22}	0.1967	0.1937	0.1941	0.1786	0.2062	0.1939
DMU_{23}	0.2875	0.3021	0.2897	0.2705	0.2559	0.2812
DMU_{24}	0.2823	0.2992	0.3333	0.3240	0.3304	0.3138
DMU_{25}	0.7851	0.7710	0.7642	0.7895	0.7747	0.7769
DMU_{26}	**0.2405**	**0.2264**	**0.2289**	**0.2039**	**0.1864**	**0.2172**
DMU_{27}	0.3743	0.3810	0.4116	0.3980	0.4038	0.3938
DMU_{28}	0.7060	0.6765	0.6573	0.6634	0.6801	0.6766
DMU_{29}	0.4041	0.4260	0.4448	0.4405	0.3855	0.4202
DMU_{30}	0.7721	0.7665	0.7577	0.7673	0.7795	0.7686
DMU_{31}	0.7224	0.6996	0.7011	0.6738	0.6721	0.6938
DMU_{32}	0.1613	0.2040	0.2686	0.2909	0.2956	0.2441

Furthermore, it can be found that all banks have a relatively stable inefficiency dominance probability in the period of 2014–2018, with the largest variation being 0.1343 (0.2956–0.1613) for Zijin Rural Commercial Bank (DMU_{32}) and the smallest variation being 0.0087 (0.7331–0.7244) for Shanghai Pudong Development Bank (DMU_{18}). All banks always have an eco-inefficiency dominance probability that is either larger than 0.50 or less than 0.50 in the five-year sample (0.5 is a threshold where the dominating probability is equal to the dominated probability), implying that all banks can be divided into two groups, one for superior banks and another for inferior banks. The categories are shown in Table 8. From the average sense, we find that China Construction Bank (DMU_9), Industrial and Commercial Bank of China (DMU_4), Industrial Bank (DMU_{25}), Bank of China (DMU_{32}), and Shanghai Pudong Development Bank (DMU_{18}) are the top five listed banks for operation performance. In contrast, the lowest five banks are Suzhou Rural Commercial Bank (DMU_{22}), Rural Commercial Bank of Zhangjiagang (DMU_{26}), Jiangyin Rural Commercial Bank (DMU_{11}), Zijin Rural Commercial Bank (DMU_{32}), and Changshu Rural Commercial Bank (DMU_2), all of which have an average inefficiency dominance probability of less than 0.2500.

The eco-inefficiency and eco-inefficiency dominance probabilities of these 32 listed banks are given in Tables 4 and 7, respectively. It is clear that the proposed approach will give performance indexes that are different from those of previous approaches. Furthermore, we give the ranking comparison of eco-inefficiency and eco-inefficiency dominance probabilities in Table 9. It can be found from Table 9 that, on the one hand, the proposed approach will give performance rankings that are largely different from those of previous approaches. On the other hand, the traditional DEA model cannot discriminate all banks, and more seriously, more than twenty banks are ranked as the first based on inefficiency scores, while the eco-inefficiency dominance probability approach can indeed give a full ranking of all banks. From this perspective, the proposed approach can give a more reasonable and discriminating performance assessment.

All 32 listed banks can be mainly categorized into four groups according to the ownership, namely, state-owned banks, joint-stock banks, city commercial banks, and rural commercial banks. Table 10 shows the divisions, and Table 11 gives the average inefficiency dominance probabilities for different kinds of banks.

Table 8: Superior and inferior listed banks.

Category	Banks
Superior (>0.5000)	Bank of Beijing, Industrial and Commercial Bank of China, China Everbright Bank, Huaxia Bank, China Construction Bank, Bank of Jiangsu, Bank of Communications, China Minsheng Bank, Bank of Nanjing, Agricultural Bank of China, Ping An Bank, Shanghai Pudong Development Bank, Bank of Shanghai, Industrial Bank, China Merchants Bank, Bank of China, China CITIC Bank
Inferior (<0.5000)	Changshu Rural Commercial Bank, Bank of Chengdu, Bank of Guiyang, Bank of Hangzhou, Jiangyin Rural Commercial Bank, Bank of Ningbo, Bank of Qingdao, Qingdao Rural Commercial Bank, Suzhou Rural Commercial Bank, Wuxi Rural Commercial Bank, Bank of Xian, Rural Commercial Bank of Zhangjiagang, Bank of Changsha, Bank of Zhengzhou, Zijin Rural Commercial Bank

Table 9: Ranking of inefficiency and inefficiency dominance probabilities.

Banks	2014		2015		2016		2017		2018	
DMU_1	1	13	1	12	1	12	1	12	1	12
DMU_2	1	26	32	28	32	31	29	30	32	29
DMU_3	1	20	25	21	29	22	1	23	25	22
DMU_4	1	2	1	2	1	2	1	2	1	2
DMU_5	1	11	23	11	1	10	25	9	23	11
DMU_6	29	24	31	24	30	24	31	22	31	20
DMU_7	26	19	1	18	1	19	1	18	1	18
DMU_8	31	14	30	15	27	16	28	16	30	15
DMU_9	1	1	1	1	1	1	1	1	1	1
DMU_{10}	1	16	1	16	1	15	1	14	1	14
DMU_{11}	1	29	1	29	1	29	1	29	1	30
DMU_{12}	25	5	1	5	1	6	1	8	1	7
DMU_{13}	1	10	1	9	1	9	1	7	1	8
DMU_{14}	28	17	26	17	25	17	1	17	26	17
DMU_{15}	30	18	28	19	26	18	27	19	28	19
DMU_{16}	27	8	1	7	1	7	1	6	1	5
DMU_{17}	1	12	1	13	1	14	1	13	1	13
DMU_{18}	23	6	1	6	1	5	1	5	1	6
DMU_{19}	1	23	1	23	23	23	1	24	1	25
DMU_{20}	1	28	1	27	1	26	1	26	1	26
DMU_{21}	1	15	1	14	1	13	1	15	1	16
DMU_{22}	1	31	1	32	1	32	26	32	1	31
DMU_{23}	1	25	1	25	1	27	1	28	1	28
DMU_{24}	1	27	1	26	1	25	1	25	1	24
DMU_{25}	1	3	1	3	1	3	1	3	1	4
DMU_{26}	1	30	1	30	1	30	1	31	1	32
DMU_{27}	1	22	27	22	28	21	32	21	27	21
DMU_{28}	1	9	1	10	1	11	1	11	1	9
DMU_{29}	1	21	1	20	24	20	24	20	1	23
DMU_{30}	1	4	1	4	1	4	1	4	1	3
DMU_{31}	24	7	24	8	1	8	1	10	24	10
DMU_{32}	32	32	29	31	31	28	30	27	29	27

It can be learned from Table 11 that the four kinds of listed banks exhibit considerably different performance dominance probabilities. More specifically, those five state-owned banks have the highest average inefficiency dominance probability, which is almost three times that of the lowest rural commercial banks. This result shows that these state-owned banks are more likely to have better performance compared with other banks over all sets of weights. In contrast, those rural commercial banks are more likely to have worse performance relative to other banks. Furthermore, joint-stock banks are inferior to state-owned banks and superior to city commercial banks, which are further superior to rural commercial banks.

By using the proposed inefficiency dominance probability approach, we can provide a performance analysis of 32 Chinese listed banks that is derived from the real world. Since the proposed approach considers all sets of feasible weights, which is different from classic DEA approaches that focus on only one or several optimal sets of weights, the resulting performance analytics are more reasonable due to taking full weights and all possibilities into account. Furthermore, by considering all sets of feasible weights, the performance dominance probability is largely different from traditional performance indexes that are obtained with some extreme weights, and the corresponding ranking orders are also changed considerably. Therefore, it makes sense for the

Table 10: Categories of different listed banks.

Category	Banks
State-owned banks (5)	Industrial and Commercial Bank of China China Construction Bank Bank of Communications Agricultural Bank of China Bank of China
Joint-stock banks (8)	China Everbright Bank, Huaxia Bank China Minsheng Bank, Ping An Bank Shanghai Pudong Development Bank Industrial Bank, China Merchants Bank China CITIC Bank
City commercial banks (12)	Bank of Beijing, Bank of Chengdu Bank of Guiyang, Bank of Hangzhou Bank of Jiangsu, Bank of Nanjing Bank of Ningbo, Bank of Qingdao Bank of Shanghai, Bank of Xian Bank of Changsha, Bank of Zhengzhou
Rural commercial banks (7)	Changshu Rural Commercial Bank Jiangyin Rural Commercial Bank Qingdao Rural Commercial Bank Suzhou Rural Commercial Bank Wuxi Rural Commercial Bank Rural Commercial Bank of Zhangjiagang Zijin Rural Commercial Bank

Table 11: Average inefficiency dominance probabilities for four kinds of listed banks.

Banks	2014	2015	2016	2017	2018	Mean
State-owned banks	0.7696	0.7676	0.7531	0.7594	0.7678	0.7635
Joint-stock banks	0.6955	0.6786	0.6731	0.6806	0.6751	0.6806
City commercial banks	0.4467	0.4577	0.4662	0.4649	0.4644	0.4600
Rural commercial banks	0.2467	0.2488	0.2508	0.2400	0.2412	0.2455

proposed approach because it can provide a comprehensive performance assessment instead of only some extreme performances from a data analytics perspective.

4. Conclusion

This paper proposes a new DEA-based approach for assessing the operation performance of Chinese listed banks. Since the conventional DEA approaches consider only a set of optimal and extreme weights to measure the relative performance, the resulting performance indexes might be unreasonable and even unrealistic in practice. From a data-driven decision-making perspective, this paper proceeds to take all sets of feasible input/output weights into account rather than only some special weights. For that purpose, we first propose an extended eco-inefficiency model to address banking activities and build a pairwise performance dominance structure in terms of inefficiency scores. Furthermore, we calculate the overall inefficiency dominance probability based on all sets of feasible weights, and the inefficiency dominance probability can be used for data-driven performance analytics of those Chinese listed banks. The proposed approach can provide data analytics on relative performances instead of only some extreme possibilities, and it is further used for the empirical analytics of operation performances for 32 listed banks in China.

This paper can be extended with regard to several aspects. First, this paper considers the possible inefficiency score range but ignores its associated possibility. That is, we consider each possible performance score coequally, but it is common that some performance scores are more likely than others. Therefore, future research can be developed to take the possibilities of various performances based on different sets of weights into account. Second, an important research avenue in the DEA field is how to address the internal production structure of DMUs, and thus, similar studies can be designed for situations with complex internal structures and linking connections. Third, similar approaches based on all sets of weights can also be developed for other purposes, such as fixed cost and resource allocation and target setting in real applications.

Data Availability

The illustration data used to support the findings of this study are collected from annual financial reports that are publicly produced by these listed banks in Shenzhen Stock Exchange and Shanghai Stock Exchange in China. In addition, the data are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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