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A COMMON WEIGHTS MODEL FOR INVESTIGATING EFFICIENCY-BASED LEADERSHIP IN THE RUSSIAN BANKING INDUSTRY

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Abstract. In this race for productivity, the most successful leaders in the banking industry are those with high-efficiency and a competitive edge. Data envelopment analysis is one of the most widely used methods for measuring efficiency in organizations. In this study, we use the ideal point concept and propose a common weights model with fuzzy data and non-discretionary inputs. The proposed model considers environmental criteria with uncertain data to produce a full ranking of homogenous decision-making units. We use the proposed model to investigate the efficiency-based leaders in the Russian banking industry. The results show that the unidimensional and unilateral assessment of leading organizations solely according to corporate size is insufficient to characterize industry leaders effectively. In response, we recommend a multilevel, multicomponent, and multidisciplinary evaluation framework for a more reliable and realistic investigation of leadership at the network level of analysis.

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1. Introduction

Globalization has converted the banking industry and, subsequently, the financial system into a vital sector of the economy [46]. Consequently, the efficiency of the banking industry has been a key driver of financial and economic development and growth [41,90,96]. Inefficient banks threaten the stability of the financial system, and banks are under constant pressure to increase their efficiency by adopting efficient banking practices, lowering their costs, improving productivity, and avoiding risky investments [8].

In this race for productivity, the most successful leaders in the banking industry are those with high profitability [29, 92], visibility [21], and competitive advantage [9]. Consequently, according to the competitive dynamics [43, 72], and the neo-institutional theoretical perspectives [25, 56], organizations in similar situations tend to

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imitate the leader's structure, processes, and strategies [48, 49]. Hence, studying the efficiency-based leadership among a set of competitive organizations such as banks is a critical task for managers who want to follow the leaders. In this regard, both parametric and non-parametric methods are widely used for efficiency analysis in the banking industry [22, 71, 74]. While parametric methods restrict the production function to a special parametric form before estimation them, non-parametric methods avoid a parametric production function and provide a clear understanding of the production possibility set [11].

One of the most applicable and popular non-parametric methods for performance measurement is the data envelopment analysis (DEA) method, which has been introduced by Charnes *et al.* [12]. The conventional DEA models consider three specific assumptions. First, they require precise input and output data. In contrast, the fuzzy and stochastic DEA models are designed to consider uncertain data in performance evaluation [57, 65]. Second, primary models with homogeneous decision-making units (DMUs) have been developed using "exogenously fixed" or non-discretionary factors for different operating environments [7, 37, 64]. Third, initial models with the ability to divide DMUs into two groups of efficient and inefficient units without providing any additional information and ranking of the efficient DMUs have been proposed for performance evaluation [4,16,36,50] in the form of common weights (CW) models [18]. We consider these three assumptions and propose a CW model for investigating efficiency-based leadership in the Russian banking industry.

The remainder of this paper is organized as follows. In Section 2, we present a review of the relevant literature review, followed by a description of the fuzzy CW model with non-discretionary inputs in Section 3. In Section 4, we present a case study to demonstrate the applicability of the proposed model. Conclusions and future research are provided in Section 6.

2. Literature review

2.1. Data envelopment analysis (DEA)

DEA is a non-parametric fractional mathematical programming method for measuring and comparing the relative efficiency as a ratio of a weighted sum of the outputs to a weighted sum of the inputs among a set of homogeneous DMUs with numerous applications in airports, hospitals, universities, banks, technologies, etc. [13,20,78,91]. In the following, the CCR (Charnes, Cooper, and Rhodes) input-oriented model of DEA proposed by Charnes *et al.* [12] is presented as the central model for development in the literature.

2.1.1. The CCR model

Using the traditional denotations in DEA and according to the research of Charnes *et al.* [12], we assume that there are a set of n DMUs and each $\mathrm{DMU}_j, (j = 1, \ldots, n)$ produces s different outputs using m different inputs which are denoted by $x_{ij}, (i = 1, \ldots, m)$ and $y_{rj}, (r = 1, \ldots, s)$, respectively. It is assumed that x_{ij} and y_{rj} are all positive. For any evaluated DMU_j, the efficiency score E can be calculated by the following CCR input-oriented multiplier model:

$$
\begin{aligned}
& E_o = \max \sum_{r=1}^{s} u_r y_{ro} \\
& \text{s.t.} \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \quad \forall j, \\
& \sum_{i=1}^{m} v_i x_{io} = 1, \\
& u_r \geq 0, v_i \geq 0, \qquad \forall r, \forall i
\end{aligned}
\tag{2.1}
$$

where the decision variables v_i and u_r are the assigned weights for the ith input and the rth output, respectively. The efficiency score for DMU_o (E_o) is calculated as the weighted sum of its outputs, while the weighted sum of its inputs equals 1.

While the conventional DEA models such as CCR require accurate measurement of both inputs and outputs, crisp input and output data may not always be relevant in real-world situations. The observed values of the input and output data in real-world problems sometimes include missing data, judgment data, or predictive data, which are generally imprecise or vague. One way to deal with the uncertain data is the consideration of fuzzy numbers in developing DEA models [6,60]. Four general approaches have been recognized in the literature for developing fuzzy DEA models [27,90]. Here we will focus on the α-level approach, which has been proposed by Saati *et al.* [65]. Although this approach is not computationally efficient, it is possibly the most popular method due to its linear computation for each α value [73]. In the following subsection, a particular case of fuzzy DEA with triangular fuzzy numbers for inputs and outputs has been proposed by Saati *et al.* [65] based on the CCR model.

2.1.2. The fuzzy CCR model

Saati *et al.* [65] define all inputs and outputs as triangular fuzzy numbers $\tilde{x}_{ij} = \left(x^l_{ij}, x^m_{ij}, x^u_{ij}\right)$ and $\tilde{y}_{rj} = \left(y^l_{rj}, y^m_{rj}, y^u_{rj}\right)$, respectively. The fuzzy CCR model using α-level approach is formulated as model (2.2) and (2.3) by defining two interval variables, including $\hat{x}_{ij} \in \left[\alpha x^m_{ij} + (1-\alpha)\, x^l_{ij}, \alpha x^m_{ij} + (1-\alpha)\, x^u_{ij}\right]$ and $\hat{y}_{rj} \in \left[\alpha y^m_{rj} + (1-\alpha)\, y^l_{rj}, \alpha y^m_{rj} + (1-\alpha)\, y^u_{rj}\right]$ where $\alpha \in (0,1]$.

$$
\begin{array}{ll}
E_o = \max \sum\limits_{r=1}^{s} u_r \hat{y}_{ro} & \\
\text{s.t.} & \\
\sum\limits_{r=1}^{s} u_r \hat{y}_{rj} - \sum\limits_{i=1}^{m} v_i \hat{x}_{ij} \leq 0, & \forall j \\
\sum\limits_{i=1}^{m} v_i \hat{x}_{io} = 1, & \\
\alpha x^m_{ij} + (1-\alpha)\, x^l_{ij} \leq \hat{x}_{ij} \leq \alpha x^m_{ij} + (1-\alpha)\, x^u_{ij}, & \forall i, \forall j, \\
\alpha y^m_{rj} + (1-\alpha)\, y^l_{rj} \leq \hat{y}_{rj} \leq \alpha y^m_{rj} + (1-\alpha)\, y^u_{rj}, & \forall r, \forall j, \\
u_r, v_i, \hat{x}_{ij}, \hat{y}_{rj} \geq 0, & \forall r, \forall i, \forall j.
\end{array}
\tag{2.2}
$$

The model includes $(n+1)(m+s)$ decision variables. Although model (2.2) is a non-linear programming (NLP) model due to the existence of non-linear terms $v_i \hat{x}_{ij}$ and $u_r \hat{y}_{rj}$, it can be transformed into the following linear programming (LP) model (2.3) using two changes in variables $\dot{x}_{ij} = v_i \hat{x}_{ij}$ and $\dot{y}_{rj} = u_r \hat{y}_{rj}$, and substituting them in model (2.2):

$$
\begin{array}{ll}
E_o = \max \sum\limits_{r=1}^{s} \dot{y}_{ro} & \\
\text{s.t.} & \\
\sum\limits_{r=1}^{s} \dot{y}_{rj} - \sum\limits_{i=1}^{m} \dot{x}_{ij} \leq 0, & \forall j, \\
\sum\limits_{i=1}^{m} \dot{x}_{io} = 1, & \\
v_i \left(\alpha x^m_{ij} + (1-\alpha)\, x^l_{ij}\right) \leq \dot{x}_{ij} \leq v_i \left(\alpha x^m_{ij} + (1-\alpha)\, x^u_{ij}\right), & \forall i, \forall j, \\
u_r \left(\alpha y^m_{rj} + (1-\alpha)\, y^l_{rj}\right) \leq \dot{y}_{rj} \leq u_r \left(\alpha y^m_{rj} + (1-\alpha)\, y^u_{rj}\right), & \forall r, \forall j, \\
u_r, v_i, \dot{x}_{ij}, \dot{y}_{rj} \geq 0, & \forall r, \forall i, \forall j
\end{array}
\tag{2.3}
$$

where $\dot{x}_{ij}$ and $\dot{y}_{rj}$ are decision variables used to convert the primary non-linear fuzzy model into a crisp parametric LP model while $\alpha \in (0,1]$ [62]. Accordingly, the model will provide an optimal solution for each α. In this model, all evaluated DMUs must be homogeneous according to the original DEA's fundamental assumptions. However, in many real-world problems, environmental diversity may violate the presumption of homogenous units [37,63]. Ruggiero [63] has demonstrated that the consequence of not controlling the environmental variables results in biased estimation of technical efficiency. In response, researchers have focused on the "exogenously fixed" or "non-discretionary" factors in their models to meet this assumption (*e.g.*, [7,35]). A CCR model with non-discretionary inputs proposed by Banker and Morey [7] is presented next to demonstrate the mathematical application of these inputs in the model.

2.1.3. The CCR model with non-discretionary inputs

Homogeneity is a fundamental assumption for all basic DEA models [7]. According to the homogeneity assumption, all DMUs must agree to the following three conditions: (i) the DMUs should execute the same processes; (ii) their efficiency should be evaluated by the same input and output variables; and (iii) all DMUs operate within the same environment under the same conditions [99]. When environmental factors cause non-homogeneity, they are considered in a single model as non-discretionary inputs. Therefore, different reference sets are defined to discriminate DMUs in different environments [7,33,63]. There is no generally accepted approach for using non-discretionary factors in DEA models. Therefore, this study considers the research of Banker and Morey [7], who proposed the CCR model by applying non-discretionary inputs k (z_{kj}), $(k = 1, \ldots, t)$ for its simplicity and popularity as the following model (2.4):

$$
\begin{aligned}
&E_o = \max \sum_{r=1}^{s} u_r y_{ro} - \sum_{k=1}^{t} w_k z_{ko,} \\
&\text{s.t.} \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{k=1}^{t} w_k z_{kj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \qquad \forall j \\
&\sum_{i=1}^{m} v_i x_{io} = 1, \\
&u_r, v_i, w_k \geq \varepsilon, \qquad \forall r, \forall i, \forall k,
\end{aligned}
\tag{2.4}
$$

where ε is a small, non-negative number used to avoid ignoring factors in calculating efficiency for DMU_o [3].

This model can be extended to situations where some non-discretionary outputs are beyond the manager's discretionary controls. In this case, increasing output is not a meaningful target for managers while there are non-controllable outputs. In other words, managers are interested in estimating the maximum possible increase in the discretionary outputs with keeping the inputs and non-discretionary outputs at their current levels. Therefore, the output-oriented objective function of the CCR model describes this situation more realistically [7].

The above DEA models evaluate the relative efficiency with favorable weights for each DMU. These efficiency scores usually lie in (0, 1]. While a ranking for inefficient DMUs is given using these models, they do not provide sufficient information about the efficient DMUs with an efficiency score of 1. Researchers have solved this problem by using various methods (*e.g.*, [4, 16, 50, 94]). Among them, the CW models are more favorable and applicable according to the literature (*e.g.*, [15, 28, 50, 76, 79, 86]). In this research, we will use the CW model based on the ideal point method proposed by Sun *et al.* [75]. The prominent feature of this method compared to competing methods, is its feasibility feature [66].

2.1.4. The CW model with ideal point approach

The CW models reduce the flexibility and the dispersion in the optimal weights assigned to the inputs and outputs by each DMU and make it possible to compare and rank the efficiency of all DMUs on the same basis [42,86]. In this study, we use the CW model based on the ideal point method proposed by Sun *et al.* [75], which provides a basic model for our final model development.

Definition 2.1. The (virtual) ideal DMU is a DMU that its inputs are at the minimum level, and its outputs are at the maximum level among all DMUs.

The ideal DMU is shown by $\text{IDMU} = (\underline{\boldsymbol{x}}, \overline{\boldsymbol{y}})$ where $\underline{\boldsymbol{x}}$ and $\overline{\boldsymbol{y}}$ respectively denote the inputs and outputs of the ideal unit, and $\underline{x}_i = \min\{x_{ij} | \forall j\}, (\forall i)$ and $\overline{y}_r = \max\{y_{rj} | \forall j\}, (\forall r)$. The CW model with ideal point method is developed next as model (2.5) based on the CCR model [44,75]:

$$
\begin{aligned}
&\theta=\min \sum_{j=1}^{n}\left[\sum_{i=1}^{m} v_i\left(x_{ij}-\underline{x}_i\right)\right]+\sum_{j=1}^{n}\left[\sum_{r=1}^{s} u_r\left(\overline{y}_r-y_{rj}\right)\right] \\
&\text{s.t.} \\
&\sum_{r=1}^{s} u_r y_{rj}-\sum_{i=1}^{m} v_i x_{ij} \leq 0, && \forall j \\
&\sum_{i=1}^{m} v_i \underline{x}_i=1, \\
&\sum_{r=1}^{s} u_r \overline{y}_r=1, \\
&v_i, u_r \geq \varepsilon, && \forall i, \forall r,
\end{aligned}
\tag{2.5}
$$

where $(\boldsymbol{v}, \boldsymbol{u}) \in \mathbb{R}^{m+s}$ is the common set of weights and the constraints $\sum_{i=1}^{m} v_i \underline{x}_i=1$ and $\sum_{r=1}^{s} u_r \overline{y}_r=1$ ensure that the IDMU is efficient. The efficiency score of DMU_j is measured by $\frac{\sum_{r=1}^{s} u_r^* y_{rj}}{\sum_{i=1}^{m} v_i^* x_{ij}}$ for $j=1,\ldots,n$, which is less than or equal to one due to the first set of constraints.

In contrast to the conventional DEA models, which must be solved n times, model (2.5) is solved one time for all units.

3. Proposed model

In this study, we propose a novel DEA model to overcome the shortfalls highlighted earlier and find a common set of weights in a fuzzy environment where the inputs $\tilde{x}_{ij}=\left(x_{ij}^l, x_{ij}^m, x_{ij}^u\right)$, non-discretionary inputs $\tilde{z}_{kj}=\left(z_{kj}^l, z_{kj}^m, z_{kj}^u\right)$, and outputs $\tilde{y}_{rj}=\left(y_{rj}^l, y_{rj}^m, y_{rj}^u\right)$ are triangular fuzzy numbers. To this aim, we define the fuzzy ideal DMU as $\text{FIDMU}=\left(\underline{\tilde{\boldsymbol{x}}}, \underline{\tilde{\boldsymbol{z}}}, \overline{\tilde{\boldsymbol{y}}}\right)$ in which:

(a) $\underline{\tilde{x}}_i=\left(\underline{x}_i^l, \underline{x}_i^m, \underline{x}_i^u\right), \underline{x}_i^b=\min\left\{x_{ij}^b \,\middle|\, \forall j\right\} \quad \forall i, \forall b \in \{l, m, u\}$.

(b) $\overline{\tilde{y}}_r=\left(\overline{y}_r^l, \overline{y}_r^m, \overline{y}_r^u\right), \overline{y}_r^b=\min\left\{y_{rj}^b \,\middle|\, \forall j\right\} \quad \forall r, \forall b \in \{l, m, u\}$.

(c) $\overline{\tilde{z}}_k=\left(\underline{z}_k^l, \underline{z}_k^m, \underline{z}_k^u\right), \underline{z}_k^b=\min\left\{z_{kj}^b \,\middle|\, \forall j\right\} \quad \forall k, \forall b \in \{l, m, u\}$.

Accordingly, the CW model with the ideal point method proposed by Sun *et al.* [75] is developed in a fuzzy environment by applying non-discretionary inputs in Models (2.3)–(2.5) and defining six interval variables, including $\hat{x}_{ij} \in [\alpha x_{ij}^m+(1-\alpha)x_{ij}^l, \alpha x_{ij}^m+(1-\alpha)x_{ij}^u]$, $\hat{\underline{x}}_i \in [\alpha \underline{x}_i^m+(1-\alpha)\underline{x}_i^l, \alpha \underline{x}_i^m+(1-\alpha)\underline{x}_i^u]$, $\hat{z}_{kj} \in [\alpha z_{kj}^m+(1-\alpha)z_{kj}^l, \alpha z_{kj}^m+(1-\alpha)z_{kj}^u]$, $\hat{\underline{z}}_k \in [\alpha \underline{z}_k^m+(1-\alpha)\underline{z}_k^l, \alpha \underline{z}_k^m+(1-\alpha)\underline{z}_k^u]$, $\hat{y}_{rj} \in [y_{rj}^m+(1-\alpha)y_{rj}^l, \alpha y_{rj}^m+(1-\alpha)y_{rj}^u]$, and $\hat{\overline{y}}_r \in [\alpha \overline{y}_r^m+(1-\alpha)\overline{y}_r^l, \alpha \overline{y}_r^m+(1-\alpha)\overline{y}_r^u]$ to propose the following NLP model:

$$
\begin{aligned}
&E_{\mathrm{IDMU}}^*(\alpha)=\min \sum_{j=1}^{n}\left[\sum_{i=1}^{m} v_i\left(\hat{x}_{ij}-\hat{\underline{x}}_i\right)+\sum_{k=1}^{t} w_k\left(\hat{z}_{kj}-\hat{\underline{z}}_k\right)+\sum_{r=1}^{s} u_r\left(\hat{\overline{y}}_r-\hat{y}_{rj}\right)\right] \\
&\text{s.t.} \\
&\sum_{r=1}^{s} u_r \hat{y}_{rj}-\sum_{i=1}^{m} v_i \hat{x}_{ij}-\sum_{k=1}^{t} w_k \hat{z}_{kj} \leq 0, && \forall j, \\
&\sum_{i=1}^{m} v_i \hat{\underline{x}}_i=1, \\
&\sum_{r=1}^{s} u_r \hat{\overline{y}}_r-\sum_{k=1}^{t} w_k \hat{\underline{z}}_k=1, \\
&\alpha x_{ij}^m+(1-\alpha)x_{ij}^l \leq \hat{x}_{ij} \leq \alpha x_{ij}^m+(1-\alpha)x_{ij}^u, && \forall i, \forall j, \\
&\alpha \underline{x}_i^m+(1-\alpha)\underline{x}_i^l \leq \hat{\underline{x}}_i \leq \alpha \underline{x}_i^m+(1-\alpha)\underline{x}_i^u, && \forall i,
\end{aligned}
\tag{3.1}
$$

$$
\begin{aligned}
&\alpha z_{kj}^m + (1-\alpha)\, z_{kj}^l \le \hat{z}_{kj} \le \alpha z_{kj}^m + (1-\alpha)\, z_{kj}^u, && \forall k, \forall j,\\
&\alpha \underline{z}_k^m + (1-\alpha)\, \underline{z}_k^l \le \underline{z}_k \le \alpha \underline{z}_k^m + (1-\alpha)\, \underline{z}_k^u, && \forall k,\\
&\alpha y_{rj}^m + (1-\alpha)\, y_{rj}^l \le \hat{y}_{rj} \le \alpha y_{rj}^m + (1-\alpha)\, y_{rj}^u, && \forall r, \forall j,\\
&\alpha \overline{y}_r^m + (1-\alpha)\, \overline{y}_r^l \le \hat{\overline{y}}_r \le \alpha \overline{y}_r^m + (1-\alpha)\, \overline{y}_r^u, && \forall r,\\
&v_i, u_r, w_k \ge \varepsilon, && \forall i, \forall r, \forall k,\\
&\hat{x}_{ij}, \hat{\underline{x}}_i, \hat{z}_{kj}, \hat{\underline{z}}_k, \hat{y}_{rj}, \hat{\overline{y}}_r \ge 0, && \forall i, \forall r, \forall k, \forall j.
\end{aligned}
\tag{3.2}
$$

The NP model (3.2) has $(n+2)\,(m+s+t)$ decision variables. We use six variable changes, including $\dot{x}_{ij} = v_i \hat{x}_{ij}$, $\dot{\underline{x}}_i = v_i \hat{\underline{x}}_i$, $\dot{z}_{kj} = w_k \hat{z}_{kj}$, $\dot{\underline{z}}_k = w_k \hat{\underline{z}}_k$, $\dot{y}_{rj} = u_i \hat{y}_{rj}$, and $\dot{\overline{y}}_k = u_r \hat{\overline{y}}_r$ to formulate the following linearized model:

$$
\begin{aligned}
&E^*_{\text{IDMU}}(\alpha) = \min \sum_{j=1}^{n} \left[\sum_{i=1}^{m} \left(\dot{x}_{ij} - \dot{\underline{x}}_i\right) + \sum_{k=1}^{t} \left(\dot{z}_{kj} - \dot{\underline{z}}_k\right) + \sum_{r=1}^{s} \left(\dot{\overline{y}}_r - \dot{y}_{rj}\right) \right]\\
&\text{s.t.}\\
&\sum_{r=1}^{s} \dot{y}_{rj} - \sum_{i=1}^{m} \dot{x}_{ij} - \sum_{k=1}^{t} \dot{z}_{kj} \le 0, && \forall j,\\
&\sum_{i=1}^{m} \dot{\underline{x}}_i = 1,\\
&\sum_{r=1}^{s} \dot{\overline{y}}_r - \sum_{k=1}^{t} \dot{\underline{z}}_k = 1,\\
&v_i \left(\alpha x_{ij}^m + (1-\alpha)\, x_{ij}^l\right) \le \dot{x}_{ij} \le v_i \left(\alpha x_{ij}^m + (1-\alpha)\, x_{ij}^u\right) && \forall i, \forall j,\\
&v_i \left(\alpha \underline{x}_i^m + (1-\alpha)\, \underline{x}_i^l\right) \le \dot{\underline{x}}_i \le v_i \left(\alpha \underline{x}_i^m + (1-\alpha)\, \underline{x}_i^u\right), && \forall i,\\
&w_k \left(\alpha z_{kj}^m + (1-\alpha) z_{kj}^l\right) \le \dot{z}_{kj} \le w_k \left(\alpha z_{kj}^m + (1-\alpha) z_{kj}^u\right) && \forall k, \forall j,\\
&w_k \left(\alpha \underline{z}_k^m + (1-\alpha)\, \underline{z}_k^l\right) \le \dot{\underline{z}}_k \le w_k \left(\alpha \underline{z}_k^m + (1-\alpha)\, \underline{z}_k^u\right), && \forall k,\\
&u_r \left(\alpha y_{rj}^m + (1-\alpha)\, y_{rj}^l\right) \le \dot{y}_{rj} \le u_r \left(\alpha y_{rj}^m + (1-\alpha)\, y_{rj}^u\right) && \forall r, \forall j,\\
&u_r \left(\alpha \overline{y}_r^m + (1-\alpha)\, \overline{y}_r^l\right) \le \dot{\overline{y}}_r \le u_r \left(\alpha \overline{y}_r^m + (1-\alpha)\, \overline{y}_r^u\right) && \forall r,\\
&v_i, u_r, w_k \ge \varepsilon, && \forall i, \forall r, \forall k,\\
&\dot{x}_{ij}, \dot{\underline{x}}_i, \dot{z}_{kj}, \dot{\underline{z}}_k, \dot{y}_{rj}, \dot{\overline{y}}_r \ge 0, && \forall i, \forall r, \forall k, \forall j.
\end{aligned}
\tag{3.3}
$$

It is evident that in this model, all DMUs consider the IDMU as the reference object. In other words, the IDMU must take the efficiency value of one, and other DMUs are compared to the IDMU for efficiency calculation in a fuzzy environment.

This model is now a crisp parametric LP problem and provides an optimal solution table for different α values, $\alpha \in (0,1]$. The model possesses $(n+2)\,(m+s+t)$ decision variables and $(2n+3)\,(m+s+t)+(n+2)$ constraints. Accordingly, if $(\boldsymbol{v}, \boldsymbol{u}, \boldsymbol{w}, \dot{\boldsymbol{x}}^*, \dot{\boldsymbol{y}}^*, \dot{\boldsymbol{z}}^*)$ is the optimal solution for model (3.3), then, we have $E_j^{*\alpha} = \frac{\sum_{r=1}^{s} \dot{y}_{rj}^* - \sum_{k=1}^{t} \dot{z}_{kj}^*}{\sum_{i=1}^{m} \dot{x}_{ij}^*}$. $E_j^{*\alpha}$ is α-efficiency score of DMU_j and the value of alpha affects efficiency scores. Also, according to model (3.3), the value of epsilon is important for its impact on the calculated weights of inputs and outputs. Note that an unsuitable value for the epsilon may lead to infeasibility [3,67]. In addition, its optimal value to reach maximum weights is another problem that needs further investigation.

Definition 3.1. DMU_j is said to be efficient at given $\alpha \in (0,1]$ if $E_j^{*\alpha} = 1$.

Theorem 3.2. *$E_j^{*\alpha_2} \le E_j^{*\alpha_1}$ for $\alpha_1 \le \alpha_2$.*

Proof. Let $S(\alpha)$ be the feasible region of the model (3.3) for a given α. It is easy to verify that $S(\alpha_2) \subseteq S(\alpha_1)$. This fact that model (3.3) is a minimization problem that completes the proof. □

The proposed model has several innovative features. Our model:

(1) provides investigators with the opportunity to address three potential concerns collectively. The first concern is uncertainty and fuzzy variables. The second concern is related to the conventional DEA limitation of not providing sufficient information for evaluating and ranking the efficient DMUs. Finally, the third concern is the homogeneity of the DMUs as a central premise in DEA modeling.
(2) provides the leadership literature with a quantitative model for measuring leadership from an efficiency perspective, which has been emphasized in previous studies [19, 30, 47, 97]. This characteristic of leadership illustrates the fact that an organization with a higher leadership index is more efficient and performs better than competing organizations [53, 61]. As a result, these high-performing organizations become role models for other competitors [29, 48].

Finally, we suggest the following model (3.4) for finding a suitable value for the epsilon in model (3.3):

$$\begin{aligned}
&\varepsilon^*(\alpha) = \max \varepsilon \\
&\text{s.t.} \\
&\sum_{r=1}^{s} \dot{y}_{rj} - \sum_{i=1}^{m} \dot{x}_{ij} - \sum_{k=1}^{t} \dot{z}_{kj} \le 0, && \forall j, \\
&\sum_{i=1}^{m} \underline{\dot{x}}_i = 1, \\
&\sum_{r=1}^{s} \overline{\dot{y}}_r - \sum_{k=1}^{t} \underline{\dot{z}}_k = 1, \\
&v_i \left(\alpha x_{ij}^m + (1-\alpha) x_{ij}^l\right) \le \dot{x}_{ij} \le v_i \left(\alpha x_{ij}^m + (1-\alpha) x_{ij}^u\right) && \forall i, \forall j, \\
&v_i \left(\alpha \underline{\dot{x}}_i^m + (1-\alpha) \underline{\dot{x}}_i^l\right) \le \underline{\dot{x}}_i \le v_i \left(\alpha \underline{\dot{x}}_i^m + (1-\alpha) \underline{\dot{x}}_i^u\right), && \forall i, \\
&w_k \left(\alpha z_{kj}^m + (1-\alpha) z_{kj}^l\right) \le \dot{z}_{kj} \le w_k \left(\alpha z_{kj}^m + (1-\alpha) z_{kj}^u\right) && \forall k, \forall j, \\
&w_k \left(\alpha \underline{\dot{z}}_k^m + (1-\alpha) \underline{\dot{z}}_k^l\right) \le \underline{\dot{z}}_k \le w_k \left(\alpha \underline{\dot{z}}_k^m + (1-\alpha) \underline{\dot{z}}_k^u\right), && \forall k, \\
&u_r \left(\alpha y_{rj}^m + (1-\alpha) y_{rj}^l\right) \le \dot{y}_{rj} \le u_r \left(\alpha y_{rj}^m + (1-\alpha) y_{rj}^u\right) && \forall r, \forall j, \\
&u_r \left(\alpha \overline{\dot{y}}_r^m + (1-\alpha) \overline{\dot{y}}_r^l\right) \le \overline{\dot{y}}_r \le u_r \left(\alpha \overline{\dot{y}}_r^m + (1-\alpha) \overline{\dot{y}}_r^u\right) && \forall r, \\
&\varepsilon - v_i \le 0, && \forall i, \\
&\varepsilon - u_r \le 0, && \forall r, \\
&\varepsilon - w_k \le 0, && \forall k, \\
&\varepsilon \ge 0 \\
&\underline{\dot{z}}_k, \dot{y}_{rj}, \overline{\dot{y}}_r \ge 0, && \forall i, \forall r, \forall k, \forall j,
\end{aligned} \tag{3.4}$$

where ε is a decision variable. This parametric LP model presents the maximum epsilon (ε^*) which applies to model (3.3) and all other values higher than ε^* cause infeasible results.

Choosing a suitable value for ε is a challenging problem in DEA (see [80, 81]). The value of ε selected in the epsilon-based DEA model influences the size of multipliers. In other words, different values of ε may lead to various efficiency assessments. Cook *et al.* [17] explained that letting $\varepsilon = \varepsilon^*$, results in an identical assessment and, more importantly, the resulting DEA model has a sharper discriminating power.

Theorem 3.3. *Model (3.4) is always feasible.*

Proof. Let $\dot{y}_{rj}^0 = \frac{1}{s} \forall r, \forall j$, $\dot{x}_{ij}^0 = \frac{1}{m} \forall i, \forall j$, $\dot{x}_{kj}^0 = \frac{1}{t} \forall k, \forall j$, $\underline{\dot{x}}_i^0 = \frac{1}{m} \forall i$, $\overline{\dot{y}}_r^0 = \frac{1}{s} \forall r$, $\underline{\dot{z}}_k^0 = \frac{1}{t} \forall k$, $v_i^0 \in \left[\frac{1}{\alpha \underline{\dot{x}}_i^m + (1-\alpha) \underline{\dot{x}}_i^u}, \frac{1}{\alpha \underline{\dot{x}}_i^m + (1-\alpha) \underline{\dot{x}}_i^l}\right] \forall i$, $w_k^0 \in \left[\frac{1}{\alpha \underline{\dot{z}}_k^m + (1-\alpha) \underline{\dot{z}}_k^u}, \frac{1}{\alpha \underline{\dot{z}}_k^m + (1-\alpha) \underline{\dot{z}}_k^l}\right] \forall k$, $u_r^0 \in \left[\frac{1}{\alpha \overline{\dot{y}}_r^m + (1-\alpha) \overline{\dot{y}}_r^u}, \frac{1}{\alpha \overline{\dot{y}}_r^m + (1-\alpha) \overline{\dot{y}}_r^l}\right] \forall r$, and $\varepsilon = \min\left\{v_i^0, w_k^0, u_r^0, \forall i, \forall k, \forall r\right\}$. Since $\alpha \underline{\dot{x}_i}^m + (1-\alpha) \underline{\dot{x}_i}^u \le \alpha x_{ij}^m + (1-\alpha) x_{ij}^u$ and $\alpha \underline{\dot{x}_i}^m + (1-\alpha) \underline{\dot{x}_i}^l \le \alpha x_{ij}^m + (1-\alpha) x_{ij}^l \forall i, \forall j$ it is easy to verify that:

$$v_i^0 \left(\alpha x_{ij}^m + (1-\alpha) x_{ij}^l\right) \le \frac{1}{m} \le v_i^0 \left(\alpha x_{ij}^m + (1-\alpha) x_{ij}^u\right), \quad \forall i, \forall j$$

and

$$v_i^0\left(\alpha\underline{\dot{x}}_i^m+(1-\alpha)\,\underline{\dot{x}}_i^l\right)\leq\frac{1}{m}\leq v_i^0\left(\alpha\underline{\dot{x}}_i^m+(1-\alpha)\,\underline{\dot{x}}_i^u\right),\quad\forall i.$$

Analogously, we obtain:

$$\begin{aligned}
&w_k^0\left(\alpha z_{kj}^m+(1-\alpha)z_{kj}^l\right)\leq\frac{1}{t}\leq w_k^0\left(\alpha z_{kj}^m+(1-\alpha)z_{kj}^u\right), && \forall k,\forall j,\\
&w_k^0\left(\alpha\underline{\dot{z}}_k^m+(1-\alpha)\underline{\dot{z}}_k^l\right)\leq\frac{1}{t}\leq w_k^0\left(\alpha\underline{\dot{z}}_k^m+(1-\alpha)\underline{\dot{z}}_{kj}^u\right), && \forall k,\\
&u_r^0\left(\alpha y_{rj}^m+(1-\alpha)y_{rj}^l\right)\leq\frac{1}{s}\leq u_r^0\left(\alpha y_{rj}^m+(1-\alpha)y_{rj}^l\right), && \forall r,\forall j,\\
&u_r^0\left(\alpha\overline{\dot{y}}_r^m+(1-\alpha)\overline{\dot{y}}_r^l\right)\leq\frac{1}{s}\leq u_r^0\left(\alpha\overline{\dot{y}}_r^m+(1-\alpha)\overline{\dot{y}}_r^u\right), && \forall r.
\end{aligned}$$

Hence, the vector $\left(\varepsilon^0,\boldsymbol{v}^0,\boldsymbol{u}^0,\boldsymbol{w}^0,\dot{\boldsymbol{x}}^0,\dot{\boldsymbol{y}}^0,\dot{\boldsymbol{z}}^0,\underline{\dot{\boldsymbol{x}}},\overline{\dot{\boldsymbol{y}}},\underline{\dot{\boldsymbol{z}}}\right)$ is a feasible solution for model (3.4). This completes the proof. □

Theorem 3.4. $\varepsilon^*\in(0,\infty)$.

Theorem 3.5. *model (3.3) is feasible for* $\varepsilon=\varepsilon^*$ *(see [82]).*

4. Case study

In this section, we study the efficiency-based leadership in 20 independent banks[1] in the Russian Federation using the method proposed in this study. The Russian banking sector has experienced considerable disorder in a highly centralized economy with the collapse of the Soviet Union. Russian banking system operates in an adverse economic environment and is dominated by large state-owned banks, which are highly fragmented and free of financial repression. The most significant feature of the modern Russian banking system is that the rules and regulations do not apply to all banks equally [45, 54, 95]. Among emerging and transition economies, the Russian banking industry has been rarely studied for performance management and efficiency.

4.1. Measurement inputs and outputs

DEA does not provide any guidelines for selecting input and output variables. Many researchers have suggested regression analysis and principal component analysis for selecting input and output variables. Deposit is a factor widely used for DEA applications in the banking industry with a dual role [31, 77, 88]. There are three approaches for designating deposits as inputs, outputs, or both (dual role). These approaches include the production approach with the aim of deposit producing, intermediation approach with the aim of profit earning, and intermediate product approach with both aims through two processes [31, 62]. Appropriate inputs are those variables that managers would like to minimize, and appropriate outputs are those with the maximizing purpose [59]. We found employees, fixed assets, and interest expenses are regularly defined as input variables (*e.g.*, [34, 58]) while loans and incomes are regularly defined as output variables (*e.g.*, [24, 40]). We performed a comprehensive review of the recent DEA applications in the banking industry presented in Table 1 to select the most suitable input and output variables for our study. We chose three discretionary inputs (x_1: number of branches, x_2: interest expense, and x_3: total expenses); two outputs (y_1: net profit and y_2: total assets as the ultimate outputs); and one non-discretionary input (z_1: branch density, which is defined as the number of branches per square kilometer and is an indicator of the space dimension for each national market). z_1 represents the availability of banking services for clients [52].

[1] The names are changed to protect the anonymity of the banks.

Table 1. Most recent DEA publications banking.

No.	Analysis	Inputs	Outputs	Reference
1	A multi-period and multi-stage DEA model using triangular type-2 fuzzy numbers for measuring the efficiencies over consecutive periods.	Employees' salaries Fixed assets Interest payments	Net interest incomes Non-performing loans	Zhou *et al.* [98]
2	DEA utilized for examining the effects of risk determinants on efficiency considering the Malmquist Productivity Index. Double Bootstrapped Truncated Regression for obtaining bias-corrected scores.	Interest expenses Operating expenses	Total income	Fernandes *et al.* [24]
3	A copula-based econometric model for identifying parameters of the structural equations and estimating technical efficiencies of the stochastic production and cost frontiers.	Labor physical capital	Total loans Investments Non-interest income	Huang *et al.* [34]
4	A new version of the modified Semi-Oriented Radial Measure model, using directional distance function and choosing a relevant direction to efficiently deal with variables with both positive and negative values.	Total non-interest expenses Other operating expenses Fixed assets Equity	Gross interest and dividend income Total non-interest operating income Loans Net income	Kaffash *et al.* [40]
5	A new DEA-based analysis framework with a regression-based feedback mechanism for providing DEA with feedback about the relevance of the inputs and the outputs.	Personnel expenses Fixed assets Equity Total interest expense	Gross loans Total customer deposits Gross income	Ouenniche and Carrales [58]
6	A fuzzy two-stage Game-DEA approach was proposed using a bargaining game model.	Personnel costs Operating costs Interest costs	Interest income Fee income Fund transfer income	Tavana *et al.* [77]
7	Two-stage network DEA model and bootstrapped truncated regression for measuring overall bank efficiency and its decomposition in intermediation and operating efficiencies.	Fixed assets Employees Loanable funds	Investments Net-interest Income Non-interest income	Gulati and Kumar [26]
8	An input-oriented profit bootstrap DEA for investigating homogeneous and heterogeneous branches according to branch size and location.	Direct operating expenses Loan loss provisions	Non-interest income Net interest income	Aggelopoulos and Georgopoulos [2]
9	DEA and stochastic frontier approach for investigating the reliability of the single frontier model	Total interest expenses Total non-interest expenses	Deposits Loans Liquid assets	Silva *et al.* [70]
10	Two approaches for selecting inputs and outputs in DEA	Employees Number of branches Assets Equity Expenses	Deposits Loans Non-interest income Interest income	Toloo and Tichy [83]
11	Fuzzy multi-objective two-stage DEA model for providing a common scale for comparing performance.	Total liability ratio Total equity ratio Unit employee cost	Profit ratio ROA ROE	Wang *et al.* [87]

TABLE 1. Continued.

No.	Analysis	Inputs	Outputs	Reference
12	Additive two-stage network DEA for disaggregating, evaluating, and testing the efficiencies.	Fixed assets Employees	Non-interest income Interest income Non-performing loans	Wang *et al.* [88]
13	The network-DEA centralized efficiency model for optimizing two stages simultaneously.	Number of branches Number of employees Personnel expenses	Equity Performance assets	Wanke and Barros [89]
14	A statistical test in the network DEA framework for assessing the importance of the risk metrics in evaluating income efficiency.	Operational costs Fixed assets Deposits Number of branches Interest costs	Non-interest earnings Interest earnings Non-performing loans	Matthews [55]
15	Three-stage data envelopment analysis with adjustment of environmental factors and statistical noise for measuring managerial efficiency and highlighting the effect of environmental criteria.	Number of operational staff Number of business personnel Branch office rent Operating expenses	Net interest spread income Net fee income	Shyu and Chiang [69]
16	An alternative DEA model that treats deposits as an intermediate product.	Fixed assets Number of employees	Total loans Other earning assets	Holod and Lewis [31]
17	DEA utilized for investigating the effect of the "First Financial Restructuring" on the operating efficiency.	Interest expense Non-interest expense Total deposits	Interest revenue Non-interest revenue Total loans	Hsiao *et al.* [32]

4.2. Data collection

We developed a database using the 2018 financial statements of the 20 banks selected for this study. In addition, we used the annual reports from the SPARK database, provided by the Interfax news agency and the Central Bank of the Russian (CBR) Federation. Russia is ideal for this study because of its largest market among the Commonwealth of Independent States countries with bank-based economies. We used the websites of the Russian banks and the CBR site to collect data on banks in this study. While the collected data were in crisp form, there were some uncertainties concerning the accuracy of the data. We also needed to consider the problem of income smoothing in financial statements [10]. In response, we decided to use fuzzy sets [93] to incorporate these uncertainties and ambiguities into our model [62]. We used triangular fuzzy numbers (a^l, a^m, a^u) to represent the uncertainties and vagueness in our data [14]. Accordingly, the collected crisp was converted into triangular fuzzy data through the following steps [62]:

(1) Considering crisp data as a^m.
(2) a^l is equal to $a^m - 1\%a^m$.
(3) a^u is equal to $a^m + 0.01\%a^m$.

The fuzzy input and output data for the Russian banks considered in this study are presented in Table 2.

5. RESULTS AND DISCUSSION

We used model (3.3) to calculate the efficiencies of 20 banks (DMUs) and normalized the results. The normalization of the efficiency scores is intended to produce efficiencies between 0 and 1 with at least one efficient unit [39, 85]. We used the GAMS program with different α values and an epsilon value of 10^{-7}. We selected

TABLE 2. Fuzzy input and output data for the Russian banks.

j	DMU	Discretionary inputs									Non-discretionary input			Outputs					
		Fixed assets*			Number of employees			Total interest expenses*			Branch density**			Total loans*			Total incomes*		
		x_{1j}^l	x_{1j}^m	x_{1j}^u	x_{2j}^l	x_{2j}^m	x_{2j}^u	x_{3j}^l	x_{3j}^m	x_{3j}^u	z_{1j}^l	z_{1j}^m	z_{1j}^u	y_{1j}^l	y_{1j}^m	y_{1j}^u	y_{2j}^l	y_{2j}^m	y_{2j}^u
1	Yekaterinburg Savings Bank	4279.59	4283.87	4284.30	2942	2945	2948	9750.50	9760.26	9761.24	0.2461	0.2464	0.2466	75 953.05	76 029.08	76 036.68	11 286.19	11 297.49	11 298.62
2	Bryansk Capital Bank	4849.40	4854.3	4854.74	3126	3129	3132	47 183.45	47 230.68	47 235.41	0.1497	0.1499	0.1500	289 210.49	289 499.99	289 528.94	41 825.82	41 867.69	41 871.88
3	Novosibirsk People Bank	5489.66	5495.2	5495.70	4155	4159	4163	132 019.77	132 151.93	132 165.14	0.2116	0.2118	0.2120	770 393.76	771 164.92	771 242.04	102 058.57	102 160.73	102 170.95
4	Northwest People Bank	6159.76	6165.9	6166.55	1597	1599	1601	18 284.86	18 303.16	18 304.99	0.0655	0.0655	0.0656	105 878.09	105 984.08	105 994.68	20 306.23	20 326.56	20 328.59
5	Northern Kazan Trust	4546.72	4551.3	4551.72	2489	2491	2493	36 814.40	36 851.25	36 854.93	0.0824	0.0825	0.0826	168 908.74	169 077.82	169 094.72	26 615.61	26 642.25	26 644.91
6	Volga National Bank	2175.86	2178.0	2178.25	2356	2358	2360	20 689.40	20 710.11	20 712.18	0.1558	0.1559	0.1561	142 651.99	142 794.78	142 809.06	24 893.54	24 918.46	24 920.95
7	Saint Peters-burg Savings Bank	3814.93	3818.8	3819.13	402	402	402	8646.19	8654.84	8655.71	0.0103	0.0103	0.0103	94 989.90	95 084.98	95 094.49	13 490.34	13 503.84	13 505.19
8	Krasnodar Financial	22 040.82	22 062.9	22 065.09	1098	1099	1100	45 863.55	45 909.46	45 914.05	0.0552	0.0552	0.0553	76 935.09	77 012.10	77 019.80	13 842.16	13 856.02	13 857.40
9	Nizhny Tagil Bank	171 073.95	171 245.2	171 262.32	27 514	27 542	27 570	153 101.83	153 255.09	153 270.41	1.4045	1.4059	1.4074	1 188 524.42	1 189 714.13	1 189 833.10	167 001.54	167 168.71	167 185.43
10	Khabarovsk Capital Bank	20 666.65	20 687.3	20 689.40	27 284	27 311	27 338	151 546.62	151 698.32	151 713.49	0.8814	0.8823	0.8832	2 259 961.67	2 262 223.89	2 262 450.12	209 868.18	210 078.26	210 099.27
11	Barnaul Bancorp	156 387.31	156 543.9	156 559.51	17 014	17 031	17 048	146 266.14	146 412.55	146 427.20	0.8729	0.8738	0.8747	687 325.34	688 013.36	688 082.16	165 074.34	165 239.58	165 256.10
12	Omsk Financial Group	4448.53	4453.0	4453.43	1131	1132	1133	3849.25	3853.10	3853.49	0.0800	0.0801	0.0802	32 749.04	32 781.83	32 785.10	4664.11	4668.78	4669.25
13	Far East Bank	4544.69	4549.2	4549.69	1075	1076	1077	57 899.59	57 957.55	57 963.34	0.0533	0.0534	0.0535	153 949.10	154 103.21	154 118.62	37 067.31	37 104.42	37 108.13
14	Siberia State Bank	2934.42	2937.4	2937.65	2139	2141	2143	36 751.65	36 788.44	36 792.12	0.1867	0.1869	0.1871	27 853.08	27 880.96	27 883.75	21 552.48	21 574.06	21 576.22
15	Union Bank of Tyumen	10 987.52	10 998.5	10 999.62	5142	5147	5152	43 426.22	43 469.69	43 474.04	0.3819	0.3823	0.3827	182 329.06	182 511.57	182 529.82	10 252.47	10 262.73	10 263.76
16	Ural Trust Bank	617.13	617.7	617.80	1337	1338	1339	35 871.19	35 907.10	35 910.69	0.0861	0.0862	0.0863	76 761.56	76 838.39	76 846.08	5077.82	5082.90	5083.41
17	First Citizens Samara	13 021.10	13 034.1	13 035.44	3796	3800	3804	93 761.98	93 855.84	93 865.22	0.1982	0.1984	0.1986	791 138.31	791 930.24	792 009.43	119 952.47	120 072.54	120 084.55
18	Makhachkala Federal	13303.38	13316.7	13318.03	3173	3176	3179	172 006.42	172 178.60	172 195.82	0.1528	0.1529	0.1531	1 168 268.60	1 169 438.03	1 169 554.98	175 498.85	175 674.53	175 692.09
19	First Chita Bank	12 494.20	12 506.7	12 507.95	10 849	10 860	10 871	93 029.14	93 122.26	93 131.57	0.4437	0.4442	0.4446	439 672.77	440 112.89	440 156.90	83 684.08	83 767.84	83 776.22
20	Cherepovets Bank	2505.83	2508.3	2508.59	3528	3532	3536	1194.31	1195.51	1195.63	0.1443	0.1444	0.1446	78 415.54	78 494.04	78 501.89	5026.33	5031.36	5031.86
FIDMU = $(\tilde{\bar{x}}, \tilde{\bar{z}}, \tilde{\bar{y}})$:		617.13	617.7	617.8	402	402	402	1194.31	1195.51	1195.63	0.0103	0.0103	0.0103	2 259 961.67	2 262 223.89	2 262 450.12	209 868.18	210 078.26	210 099.27

Notes. *In Millions of Russian Rubles. **In 10^{-3} number per km^2.

Table 3. Normalized efficiency scores and rankings of the Russian banks.

j	DMU	Efficiency scores*							
		$\alpha = 0.25$	Rank	$\alpha = 0.5$	Rank	$\alpha = 0.75$	Rank	$\alpha = 1$	Rank
1	Yekaterinburg Savings Bank	0.069623	18	0.069622	18	0.069621	18	0.06962	18
2	Bryansk Capital Bank	0.243749	6	0.243748	6	0.243748	6	0.243748	6
3	Novosibirsk People Bank	0.453649	5	0.45365	5	0.453651	5	0.453652	5
4	Northwest People Bank	0.222637	7	0.222618	7	0.222599	7	0.22258	7
5	Northern Kazan Trust	0.192283	9	0.192289	9	0.192295	9	0.192302	9
6	Volga National Bank	0.187337	10	0.187341	10	0.187343	10	0.187347	10
7	Saint Petersburg Savings Bank	0.612904	2	0.61305	2	0.613196	2	0.613342	2
8	Krasnodar Financial	0.222145	8	0.222145	8	0.222146	8	0.222146	8
9	Nizhny Tagil Bank	0.111105	15	0.111104	15	0.111102	15	0.1111	15
10	Khabarovsk Capital Bank	0.152525	13	0.152527	13	0.152529	13	0.152531	13
11	Barnaul Bancorp	0.165635	11	0.165631	11	0.165626	11	0.16562	11
12	Omsk Financial Group	0.07534	17	0.075341	17	0.075343	17	0.075343	17
13	Far East Bank	0.587567	3	0.58756	3	0.587552	3	0.587544	3
14	Siberia State Bank	0.159976	12	0.15997	12	0.159965	12	0.159958	12
15	Union Bank of Tyumen	0.045352	19	0.045353	19	0.045356	19	0.045358	19
16	Ural Trust Bank	0.08212	16	0.082128	16	0.082135	16	0.082143	16
17	First Citizens Samara	0.571191	4	0.571175	4	0.57116	4	0.571144	4
18	Makhachkala Federal	1	1	1	1	1	1	1	1
19	First Chita Bank	0.135226	14	0.135223	14	0.13522	14	0.135216	14
20	Cherepovets Bank	0.031122	20	0.031122	20	0.031122	20	0.031121	20

Notes. *Normalized efficiency scores are calculated for $\alpha \in (0, 1]$ and $\varepsilon = 10^{-7}$.

this non-maximum value for epsilon arbitrarily to achieve feasible solutions due to the large values. However, epsilon's optimal value is influential in measuring the weights and producing results with more discriminating power [17].

Table 3 illustrates the normalized efficiency scores of the 20 banks and their ranks for different values of alpha in columns 3–12. The results demonstrate that all 20 banks are inefficient, and their efficiency values have decreased substantially because of using the CW approach and the ideal point method in efficiency evaluation. This method will consider a virtual ideal unit as the reference object with the lowest inputs and highest outputs. This ideal unit will be considered our ideal efficient DMU with an efficiency score of one [75]. There is a large difference between the efficiency of the ideal unit and all other DMUs.

In the last step, model (3.4) is used to obtain the maximum value of epsilon for model (3.3). Other values greater than ε^* produce infeasible results [82]. Accordingly, the epsilon's optimal values (maximum epsilon) were estimated for $\alpha \in (0, 1]$ and applied to recalculate the efficiency scores in the case study, and their value is presented in Table 4. Again, we have normalized the efficiency scores to avoid small efficiencies derived from the implementation of the CW model and the ideal unit method.

A graphical representation of the recalculated efficiency scores for the optimal epsilon values is presented in Figure 1. The majority of the DMUs have the same rankings for different alpha values due to the adjustments of the weights for achieving optimal answer for $E^*_{\mathrm{IDMU}}(\alpha)$ in a CW model when there is no flexibility for weights.

As shown in Tables 3 and 4, the efficiency scores of the proposed model decrease with the implementation of ε^*, and all DMUs obtain different rankings. Also, the efficiency scores in Table 4 follows a different trend. The efficiency scores for the majority of the DMUs decrease with increasing alpha from zero to 0.5 and then follow an increasing trend.

The results in Table 3 show that by using a lower value for the epsilon in model (3.3), the Makhachkala Federal Bank with an efficiency score of 1 is the best DMU even with lower corporate size (around 3170 employees) in

TABLE 4. Normalized recalculated efficiency scores and rankings of the Russian banks.

j	DMU	Efficiency scores*							
		$\alpha = 0.25$ $\varepsilon^* = 4.047 \times 10$	Rank	$\alpha = 0.5$ $\varepsilon^* = 4.422 \times 10$	Rank	$\alpha = 0.75$ $\varepsilon^* = 4.421 \times 10$	Rank	$\alpha = 1$ $\varepsilon^* = 4.420 \times 10$	Rank
1	Yekaterinburg Savings Bank	0.128967	14	0.127221	13	0.127222	13	0.127222	13
2	Bryansk Capital Bank	0.431073	7	0.426641	7	0.426641	7	0.426641	7
3	Novosibirsk People Bank	1	1	1	1	1	1	1	1
4	Northwest People Bank	0.129593	13	0.123205	14	0.123205	14	0.123206	14
5	Northern Kazan Trust	0.271678	8	0.265887	8	0.265887	8	0.265887	8
6	Volga National Bank	0.486234	5	0.468991	5	0.468993	5	0.468996	5
7	Saint Petersburg Savings Bank	0.179926	12	0.178515	12	0.178515	12	0.178515	12
8	Krasnodar Financial	0.026062	20	0.025027	20	0.025027	20	0.025027	20
9	Nizhny Tagil Bank	0.050153	18	0.049827	18	0.049827	18	0.049827	18
10	Khabarovsk Capital Bank	0.755002	3	0.782661	3	0.782663	3	0.782665	3
11	Barnaul Bancorp	0.0345	19	0.031521	19	0.031521	19	0.031521	19
12	Omsk Financial Group	0.053232	17	0.052798	17	0.052798	17	0.052798	17
13	Far East Bank	0.265247	9	0.242162	10	0.242163	10	0.242164	10
14	Siberia State Bank	0.106244	16	0.067849	16	0.067849	16	0.067849	16
15	Union Bank of Tyumen	0.110847	15	0.118905	15	0.118905	15	0.118906	15
16	Ural Trust Bank	0.827162	2	0.877927	2	0.877942	2	0.877958	2
17	First Citizens Samara	0.442172	6	0.434996	6	0.434997	6	0.434998	6
18	Makhachkala Federal	0.637418	4	0.627753	4	0.627754	4	0.627756	4
19	First Chita Bank	0.264653	10	0.251886	9	0.251886	9	0.251887	9
20	Cherepovets Bank	0.210726	11	0.224387	11	0.224389	11	0.22439	11

Notes. *Normalized recalculated efficiency scores are obtained with $\alpha \in (0, 1]$ and the maximum ε.

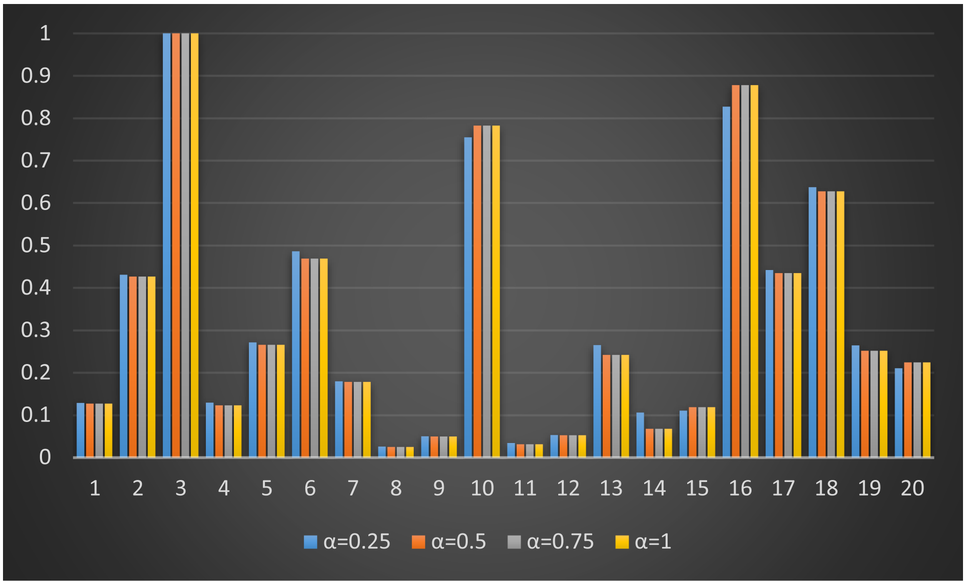

FIGURE 1. Efficiency scores with different alpha levels.

comparison with Nizhny Tagil Bank (around 27 550 employees) and Khabarovsk Capital Bank (around 27 300 employees). However, this result is different when we selected ε^* as the optimal value of the epsilon in model (3.3). In this situation, the Novosibirsk People Bank, with an efficiency of 1 has the highest efficiency among the 20 banks. The results demonstrate that focusing on unidimensional and unilateral attributes like the firm size [23, 68] is not sufficient for successfully characterizing leaders. Consequently, most literature reviews have concluded that trait theories have fallen out of interest between researchers in the leadership area [38]. We advocate a multilevel, multicomponent, and multidisciplinary approach to leadership [1, 5, 51, 84] for achieving robust and reliable results.

6. Conclusions and future research

In this paper, we highlighted three shortcomings in the existing DEA models and used non-discretionary inputs and fuzzy data in a CW model with an ideal point method to measure efficiency in the Russian banking industry. We also considered uncertainties inherent in real-world data and used fuzzy sets to take into account these uncertainties. In addition, we considered non-discretionary inputs to incorporate the homogeneity of the DMUs in our model. We used the proposed CW model and ranked 20 independent banks in the Russian Federation. Finally, we used our model to find the efficiency-based leaders in the Russian banking industry. The results show a unidimensional and unilateral assessment of leading organizations merely according to corporate size is not sufficient to effectively characterize industry leaders.

As for further research, we suggest developing a multidimensional DEA model considering different weights for different dimensions. This will allow us to include various characteristics of leadership based on the existent theories in the forms of different dimensions of inputs and outputs.

Declaration of interest. The authors declare no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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