Часопис из области економије, менаџмента и информатике
БизИнфо (БЛАЦЕ)
www.bizinfo.edu.rs
Journal of Economics, Management and Informatics
BizInfo (BLACE)

Assessing banks efficiency: DEA implementation

Procena efikasnosti banaka: Implementacija DEA modela

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Article info

Original scientific paper/ Originalan naučni rad

Received/ Rukopis je primljen:
20 May, 2024
Revised/ Korigovan:
20 December, 2024
Accepted/ Prihvaćen:
18 January, 2025
Published online: 2 February, 2025

DOI:
https://doi.org/10.71159/bizinfo250003I

UDC/ UDK:

Abstract

By examining intermediate, operating, and profitability aspects, this paper aims to construct a performance model for evaluating the relative efficiency and potential for improvement of 20 banks operating in Serbia for the 2022-2023 period. Data Envelopment Analysis (DEA), which belongs to relatively new data-oriented techniques, was used in the research to measure efficiency. To achieve its goals, the paper makes use of the CCR and BCC, two fundamental DEA models, and three approaches: intermediary, operating and profitability. The results of the analysis showed that the highest efficiency can be attributed o the use of the intermediate approach, while the lowest efficiency of banks can be attributed to the profitability approach. Additionally, the BCC model has higher efficiency compared to the CCR model. According to the analysis results, efficiency has generally grown and is comparatively stable.
***Keywords**: DEA, Intermediary approach, operating approach, profitability approach, technical efficiency, scale efficiency, Serbian banking sector*

Sažetak

Ispitujući intermedijarne, operativne i aspekte profitabilnosti, ovaj rad ima za cilj da konstruiše model performansi za procenu relativne efikasnosti i potencijala za unapređenje 20 banaka, koje posluju u Srbiji, za period od 2022 do 2023. godine. Za merenje efikasnosti, u istraživanju je primenjena analiza obavijanja podataka (DEA), koja spada u red relativno novih tehnika. Radi postizanja ciljeva u radu su korišćeniCCR i BCC model, dva osnovna DEA modela, i tri pristupa: intermedijarni, operativni i pristup profitabilnosti. Rezultati analize su pokazali da je najveća efikasnost ostvarena primenom intermedijarnoog pristupa, dok je najmanja efikasnost banaka prema pristupu profitabilnosti. Pored toga, BCC model ima veću efikasnost u poređenju sa CCR modelom. Prema rezultatima analize, efikasnost je generalno porasla i relativno je stabilna.
***Ključne reči**: DEA, intermedijarni pristup, operativni pristup, pristup profitabilnosti, tehnička efikasnost, efikasnost obima, Srpski bankarski sektor*

1. Introduction

Over the past 40 years, performance, in all its manifestations, has been the focus of a growing number of interdisciplinary research projects. Performance on an individual, group, and organizational level is valued highly and should be improved. Governments and their policies become more result-oriented when management by performance is implemented in order to make the best use of limited resources, maintain, for example, competitiveness in the private sector, or increase value for money. Organizations of all kinds are under pressure in this competitive, globalized world of interconnected financial markets, crises, and shockwaves. This demands more resilience and performance awareness, particularly with regard to measurement, monitoring, and ultimately the identification of inefficiencies inside the company. The emergence of performance management approaches and academic fervor have coincided with managers' growing interest in performance. “Decision Making Units” (DMUs) are typically defined to quantify relative efficiency, with a diverse species of methodologies at hand, in order to undertake benchmarking between different businesses (Lampe & Hilgers, 2015).

Global economic progress is significantly influenced by the banking industry. In particular, the banking industry's financial intermediation activities are crucial to the

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execution of development initiatives. Accordingly, to guarantee macroeconomic stability and economic growth, commercial banks must develop in a balanced manner. Amado et al. (2012) emphasized that efficiency measures are essential to achieving sustainable development in a system that is competitive. Since its introduction by Charnes, Cooper, and Rhodes in 1978, data envelopment analysis (DEA) has been extensively used to analyze the efficiency of banks.

The subject of this paper is the assessment of the efficiency of banks using the DEA method. In the line with the subject, the aim of the paper is to assess the efficiency of banks operating in Serbia, by applying and comparing different DEA models (CCR and BCC) and approaches (intermediary, operating and profitability). The importance of the preformed analysis is multiple, because it provides insight into the efficiency of the Serbian banking sector, as well as each bank individually (Marcikic Horvat et al., 2022a). The paper is organized as follows to address the research objectives: A literature reviewis given after the introduction. The following section of the paper presents the research methodology. The findings of the DEA's examination of the banks are included in the results section. In the discussion section the research findings are covered. The paper's last section includes important conclusions, real-world applications, restrictions, and suggestions for additional study on the subject.

2. Literature review

Since Charnes, Cooper, and Rhodes (1978) applied data envelopment analysis (DEA) for the first time, DEA analyses have been applied in every area of economics (Emrouznejad and Jang, 2018; Ahn et al., 2018). Using a variety of performance indicators divided into "inputs" and "outputs," data envelopment analysis (DEA) is used to evaluate the effectiveness of decision-making units (DMUs) (Charnes et al., 1978; Banker et al., 1984). Enhancing the decision making units' (DMU) outputs is the main goal of DEA application. The radial, additive, and slack-based measure models are the three fundamental DEA models that are used. DEA models are becoming more and more used in the measurement of microfinancial institutions' efficiency, including banks, insurance providers, financial holding companies, and others (Berger & Humphrey, 1997; Lukić et al., 2020; Nourani et al., 2021; Banker et al., 2022; Raj et al., 2023).

The following factors determine the specification of a DEA model: 1) the optimization task's objective (profit maximization or cost minimization); 2) returns-to-scale assumptions (constant returns to scale - CRS or variable returns to scale - VRS); and 3) the specification of a conceptual approach to business, which designates a combination of model inputs and outputs. There is disagreement among researchers over the scale assumption. The CRS assumption (Charnes et al., 1978) under which the original DEA model (CCR model) was built states that "t times increase in inputs will result in t times increase in output" (Fethi and Pasiouras 2010). Subsequently, the model was changed to incorporate the VRS assumption into the BCC model (Banker et al., 1984). According to the VRS assumption, "a greater (or less) than equiproportionate increase in output is yielded by equally proportionate increases in factor inputs" (Heffernan, 2005). According to experts, CRS is only applicable to businesses that run at optimal scale (Coelli et al., 1998). Consequently, in several sectors (such as the banking industry), variables like inadequate competition or governmental policies can lead to a departure from an ideal scale (Coelli et al., 1998; Beccalli et al., 2006; Singh et al., 2008). In addition, VRS is thought to be a more suitable premise for gauging efficiency in the advanced banking industry (McAllister & McMaus, 1993; Wheelock & Wilson 1995).

The most commonly discussed topic in articles pertaining to DEA is how to determine the model variables, or the mix of inputs and outputs. In general, minimally desirable inputs are those that should be minimized, and maximally desired outputs are those that should be maximized. Both input and output orientations can be used in the DEA model to solve the issue (Thagunna & Poudel, 2013). The outputs are maximized in an output-oriented model whereas the inputs are minimized in an input-oriented model. Three fundamental banking approaches - the intermediation method, the production approach, and the profitability approach - are the main criteria used in the selection process. The intermediary technique gauges how well loans and other placements are made from the available sources since it is predicated on the intermediation, which is the bank's core purpose. Also known as the production approach, the operating approach takes the effectiveness of banking operations into account. This strategy seeks to keep bank operating expenses to a minimum. The value-added approach, often known as profitability, is used to gauge how effectively banks generate revenue. It is frequently employed in the measuring of bank performance due to the significance of profit in financial organizations such as banks (Marcikic Horvat et al., 2022b).

A key concern for every DEA model is the selection of variables. This is due to the fact that banks actually use a wide range of inputs to produce profits (Zhou et al., 2018). According to Sealey and Lindley (1977), who emphasize the intermediary role of banks, deposits, labor, and capital are viewed as inputs, while loans and securities are treated as outputs. According to Heffernan (2005), the production method assumes that banks use labor and capital to produce a variety of financial goods, including deposits and loans. The production strategy and the profitability approach are somewhat comparable, but the profitability approach's outputs - such as interest and non-interest income - are more focused on profit (Thagunna and Poudel 2013). According to the findings of the literature research on DEA, deposits are essentially viewed as inputs, meaning that the intermediation approach is given priority (Beccalli et al., 2006; Nigmonov, 2010; Shahooth & Battall 2006; Singh et al., 2008; Thagunna & Poudel, 2013). In Zhou et al. (2018), deposits are the only output during the production stage; staff and interest costs should be used as inputs. Bank deposits from the production stage are treated as inputs in the profitability stage, and loans, interest, and non-interest profits are used as desired outputs while non-performing loans are used as unwanted outputs. In Milenkovic et al. (2022) research, deposits, labor cost, and capital were used as inputs, and loans and investments were used as outputs. They applied an intermediate approach. The DEA model variables used in the most recent studies on bank performance measurement are shown in Table 1.

Table 1. Input and output combinations used in DEA models

Source	Input	Output
Thagunna & Poudel, 2013	Deposits Interest expense Operating non-interest expense	Total loans Interest income Operating non-interest income
Eriņa & Eriņš, 2013	Labour Capital	Loans Deposits
Wang et al., 2014	Deposits	Non-interest income, and Interest income Non-performing loans
Titko et al., 2014	Deposits from customers Balances due to credit institutions Equity Interest expense Commission expense Staff expense Total administrative expense	Loans Securities Interest income Commission income Operating profit Net interest margin
Boďa & Zimková, 2015	Total deposits Total capital Operating expenses	Total loans Net interest income
Milenković et al., 2022	Deposits Labor Capital	Loans Investments
Marcikić Horvat et al., 2022a	Loans Investments	Interest income Non-interest income Net-income
Ullah et al., 2023	No of employees No of branches Adm. expenses Non-interest expense Loan Loss provisions	Net-interest income Net commission Total other income

Source: The authors, based on a literature review

3. Data and methodology

This paper analyses the efficiency of the banking sector in Serbia during the during the 2022-2023 period by examining the relationship between the inputs used and the outputs achieved. As a result, Data Envelopment Analysis (DEA) is a well-liked and useful technique for evaluating the effectiveness of different decision-making units (DMUs). When achieving maximum outputs, DEA often presents the efficiency of DMUs in maximizing outputs while utilizing minimum or minimal inputs. Furthermore, DEA is carried out using known and current input and output data. The banks operating in the Serbian market in 2022 and 2023 will be identified as distinct DMUs in this analysis, and the intermediary, operating, and profitability approaches will be used to determine each bank's efficiency. These approaches, as shown in Table 1, use different input and output variables but employ the same DEA methodology.

Table 2. An explanation of efficiency-oriented methods

Intermediary approach	Operating approach	Profitability approach
Inputs: Deposits, Labor cost, Capital	Inputs: Interest expenses, Labor cost, non-interest expenses	Inputs: Loans, Investments
Outputs: Loans, Investments	Outputs: Interest income, non-interest income	Outputs: Interest income, non-interest income, Net-income

Source: Author's presentation, based on Marcikić Horvat et al., 2022a

Annual data were gathered from Serbia's National Bank databasecovering the 2022-2023 period,. Tables 3 and 4 provide descriptive statistics for each input and output variable. According to the descriptive statistics, there were no appreciable shifts in the input and output variable values over the two years under consideration. As shown in Table 3, the highest mean value was recorded for the variable deposits, where the highest dispersion of results was recorded. The smallest mean value recorded for the variable interest expenses, where the smallest standard deviation was recorded.

According to the results, shown in Table 4, the highest mean value was recorded for the variable deposits, and the lowest for the variable capital. The highest dispersion of results was recorded for the variable deposits, and the lowest for the variable Non-interest expenses. Table 4 shows more detailed information.

Table 3. Descriptive statistics for input and output variables in 2022 (in 000 RSD)

Variables	Minimum	Maximum	Standard deviation	Mean
Deposits	3168930.00	704945050.00	222035539.75	225054669.66
Capital	178034.00	7493706.00	2325474.80	2202400.58
Loans	1999852.00	100357986.00	35183868.75	36357258.26
Investments	2390756.00	583295001.00	171125400.15	181416646.35
Labor cost	33940.00	11735516.00	3394719.35	3647834.37
Interest income	187791.00	27175122.00	8782072.30	8786604.91
Interest expenses	25015.00	6037982.00	1556532.50	1683017.14
Non-interest income	61097.00	25287972.00	5257064.35	6495089.13
Non-interest expenses	6669.00	11898220.00	1894821.60	2828789.41
Net income	163816.00	33907250.00	9791885.95	10274955.24

Source: Author's calculation

Table 4. Descriptive statistics for input and output variables in 2023 (in 000 RSD)

Variables	Minimum	Maximum	Standard deviation	Mean
Deposits	3348386.00	778140758.00	246742603.35	250747050.92
Capital	182021.00	8510974.00	2780002.55	2534589.45
Loans	2282799.00	110818201.00	40897574.90	41550147.45
Investments	3045514.00	691148234.00	195825140.50	209557318.80
Labor cost	88287.00	12018055.00	3738654.55	3914500.22
Interest income	272717.00	47607781.00	15649144.35	15826662.79
Interest expenses	33572.00	17933841.00	4268784.65	4965074.02
Non-interest income	63616.00	26181184.00	5877629.05	7047045.03
Non-interest expenses	4867.00	11958751.00	2011365.45	2907050.20
Net income	260106.00	45270576.00	14127249.25	14889714.69

Source: Author's calculation

DEA primarily addresses the effectiveness of a single unit, which Charnes et al. (1978) described as a Decision Making Unit (DMU). Every DMU (in this case, Serbian banks) handles problems relating to the transformation of inputs into outputs, which can happen as a result of operational and strategic choices. The foundation of DEA is the idea of engineering efficiency (Yue, 1992), which is defined as follows:

$$Efficiency\ (\theta) = \frac{Weighted\ \ sum\ of\ outputs}{Weighted\ \ sum\ of\ inputs}$$

If a DMU can produce the same amount of output with fewer inputs or more output with the same or fewer inputs, then it is considered reasonably efficient compared to other DMUs. The efficiency score is a number between 0 and 1, and a DMU is considered efficient if it has a maximum efficiency score of 1.

A DEA model with a variable return to scale was selected and used in this work. For every DMU and every time period, the following linear programming model - created by Banker, Charnes, and Cooper in 1984 - was solved in order to conduct the analysis:

$$\max \Phi$$
$$s.t. \sum_{j=1}^{n} x_{ij}\lambda_j \le x_{io} \qquad i = 1,2, \dots, m;$$
$$\sum_{j=1}^{n} y_{rj}\lambda_j \le y_{ro} \qquad r = 1,2, \dots, s;$$
$$\sum_{j=1}^{n} \lambda_j = 1$$
$$\lambda_j \ge 0$$

where: Φ - the efficiency score; n - the number of entities (DMUs) in the sample (in this case, banks)in Serbia); DMUo - the bank under evaluation; m - the number of input variables; s - the number of output variables; y_r and x_i - the observed output and input values, y_{ro} - the output r that DMUo uses, and x_{io} - the input i that DMUo uses; λ - an entity's weight (DMU).

4. Results

For assessing bank efficiency, the output-oriented CCR model, based on the intermediary approach (Tables 5 and 6), was first considerεd. The CCR model does not take scale efficiency into consideration. When given the same amount of input, banks with efficiency scores of less than one are not producing at the same level as those with scores of one. It implies that banks that have a score below one can raise their production. For example, Adriatic Bank's efficiency score for the 2022 was 0.77 (Table 5). This suggests that, given the same amount of inputs, Adriatic Bank could improve its outputs by 23% (1-0.77). Also, in 2022, 5 out of 20 banks were fully efficient, while 15 banks had an average efficiency of 0.84. Mobi and MiraBank were the least efficient in 2022.The BCC model, which takes returns to scale into consideration and divides and establishes scale efficiency and technical efficiency, is a straightforward extension of the DEA CCR model. The efficiency scores for the output-oriented BCC model for 2022 were determined using this model (Table 5). To facilitate comparison, the efficiency scores for the CCR and BCC models are shown. The BCC model represents "pure" technical efficiency, yet such technically efficient banks might not be scalable. Among these banks are API, Intesa, Postanska Stedionica, Eurobank Direktna, Alta, MiraBank, NLB Komericijalna, OTP and Unicredit bank. The banks that are technically efficient and functioning on the most suitable returns to scale are AIK, BOC, 3 Banka, Procredit, and Srpska bank.

Based on the the output-oriented CCR model, in 2023, 10 out of 20 banks were fully efficient. BOC bank was the least efficient in 2023. The efficiency scores for the output-oriented BCC model for 2023 were determined using this model (Table 6). To facilitate comparison, the efficiency scores for the CCR and BCC models are shown. Banks that, regardless of purely technical efficiency, are not efficient at the level: API, Postanska Stedionica, NLB Komericijalna, and Unicredit bank. The banks that are technically efficient and functioning on the most suitable returns to scale are AIK, Intesa, Eurobank Direktna, Adriatic, Halk, MiraBank, OTP, 3 Banka, Procredit, and Srpska bank.

Table 5. DEA output-oriented CCR and BCC model, and Scale Efficiency results: Intermediary Approach (in 2022)

DMU	Score CRS (Technical Efficiency)	Rank	Score VRS (Pure Technical Efficiency)	Rank	Scale Efficiency
API	0.697	18	1	1	0.697
ADDIKO	0.963	7	0.974	14	0.987
AIK	1	1	1	1	1
INTESA	0.919	10	1	1	0.919
BOC	1	1	1	1	1
POSTANSKA STEDIONICA	0.888	12	1	1	0.888
ERSTE	0.837	14	0.895	17	0.935
EUROBANK DIREKTNA	0.961	8	1	1	0.961
ADRIATIC BANK	0.765	16	0.860	18	0.890
HALK	0.888	11	0.906	16	0.980
ALTA	0.863	13	0.947	15	0.911
MIRABANK	0.686	19	1	1	0.686
NLB KOMERCIJALNA BANKA	0.834	15	1	1	0.834
OTP	0.975	6	1	1	0.975
3 BANKA	1	1	1	1	1
PROCREDIT	1	1	1	1	1
RAIFFEISEN	0.733	17	0.791	19	0.926
SRPSKA	1	1	1	1	1
MOBI	0.659	20	0.696	20	0.946
UNICREDIT	0.932	9	1	1	0.932
Mean	0.880		0.953		0.923

Source: Author's calculation

Table 6. DEA output-oriented CCR and BCC model, and Scale Efficiency results: Intermediary Approach (in 2023)

DMU	Score CRS (Technical Efficiency)	Rank	Score VRS (Pure Technical Efficiency)	Rank	Scale Efficiency
API	0.743	19	0.911	15	0.815
ADDIKO	0.988	11	0.990	14	0.998
AIK	1	1	1	1	1
INTESA	1	1	1	1	1
BOC	0.665	20	0.802	20	0.829
POSTANSKA STEDIONICA	0.804	17	1	1	0.804
ERSTE	0.890	14	0.891	16	0.999
EUROBANK DIREKTNA	1	1	1	1	1
ADRIATIC BANK	1	1	1	1	1
HALK	1	1	1	1	1
ALTA	0.762	18	0.837	19	0.909
MIRABANK	1	1	1	1	1
NLB KOMERCIJALNA BANKA	0.945	12	1	1	0.945
OTP	1	1	1	1	1
3 BANKA	1	1	1	1	1
PROCREDIT	1	1	1	1	1
RAIFFEISEN	0.851	15	0.852	18	0.999
SRPSKA	1	1	1	1	1
MOBI	0.811	16	0.889	17	0.913
UNICREDIT	0.936	13	1	1	0.936
Mean	0.919		0.958		0.957

Source: Author's calculation

For assessing bank efficiency, the output-oriented CCR model, based on the operating approach (Tables 7 and 8), was considered. Based on this model results, in 2022, 10 out of 20 banks were fully efficient.. Mobi, API, and Srpska bank were the least efficient in 2022. The efficiency scores for the output-oriented BCC model for 2022 were determined using this model (Table 7). To facilitate comparison, the efficiency scores for the CCR and BCC models are shown. Banks that, regardless of pure technical efficiency, are not efficient at the level: Eurobank Direktna, MiraBank, OTP, and Srpska bank. The banks that are technically efficient and functioning on the most suitable returns to scale are Addiko, AIK, Intesa, BOC, Alta, NLB Komercijalna banka, 3 Banka, Procredit, Raiffeisen, and Unicredit bank.

Based for the output-oriented CCR model, in 2023, 7 out of 20 banks were fully efficient. Mobi and Adriatic bank were the least efficient in 2023. The efficiency scores for the output-oriented BCC model for 2023 were determined using this model (Table 8). To facilitate comparison, the efficiency scores for the CCR and BCC models are shown. Banks that, regardless of purely technical efficiency, are not efficient at the level: Addico, Intesa, Eurobank Direktna, Alta, MiraBank, and OTP bank. The banks that are technically efficient and functioning on the most suitable returns to scale are AIK, BOC, NLB Komercijalna banka, 3 Banka, Raiffeisen, Srpska, and Unicredit bank.

Table 7. DEA output-oriented CCR and BCC model, and Scale Efficiency results: Operating Approach (in 2022)

DMU	Score CRS (Technical Efficiency)	Rank	Score VRS (Pure Technical Efficiency)	Rank	Scale Efficiency
API	0.576	19	0.708	18	0.813
ADDIKO	1	1	1	1	1
AIK	1	1	1	1	1
INTESA	1	1	1	1	1
BOC	1	1	1	1	1
POSTANSKA STEDIONICA	0.683	16	0.701	19	0.973
ERSTE	0.938	12	0.953	15	0.984
EUROBANK DIREKTNA	0.847	13	0.965	14	0.878
ADRIATIC BANK	0.712	14	0.798	16	0.892
HALK	0.712	15	0.736	17	0.966
ALTA	1	1	1	1	1
MIRABANK	0.648	17	1	1	0.648
NLB KOMERCIJALNA BANKA	1	1	1	1	1
OTP	0.986	11	1	1	0.986
3 BANKA	1	1	1	1	1
PROCREDIT	1	1	1	1	1
RAIFFEISEN	1	1	1	1	1
SRPSKA	0.584	18	0.998	13	0.585
MOBI	0.545	20	0.563	20	0.967
UNICREDIT	1	1	1	1	1
Mean	0.861		0.921		0.934

Source: Author's calculation

Table 8. DEA output-oriented CCR and BCC model, and Scale Efficiency results: Operating Approach (in 2023)

DMU	Score CRS (Technical Efficiency)	Rank	Score VRS (Pure Technical Efficiency)	Rank	Scale Efficiency
API	0.706	15	0.718	16	0.983
ADDIKO	0.862	13	1	1	0.862
AIK	1	1	1	1	1
INTESA	0.885	10	1	1	0.885
BOC	1	1	1	1	1
POSTANSKA STEDIONICA	0.589	18	0.626	19	0.939
ERSTE	0.865	12	0.893	15	0.968
EUROBANK DIREKTNA	0.761	14	0.908	14	0.837
ADRIATIC BANK	0.430	19	0.641	18	0.671
HALK	0.653	17	0.696	17	0.937
ALTA	0.930	8	0.970	12	0.958
MIRABANK	0.671	16	1	1	0.671
NLB KOMERCIJALNA BANKA	1	1	1	1	1
OTP	0.881	11	1	1	0.881
3 BANKA	1	1	1	1	1
PROCREDIT	0.900	9	0.926	13	0.972
RAIFFEISEN	1	1	1	1	1
SRPSKA	1	1	1	1	1
MOBI	0.387	20	0.440	20	0.879
UNICREDIT	1	1	1	1	1
Mean	0.826		0.891		0.922

Source: Author's calculation

In the third analysis, the output-oriented CCR model, which is based on the profitability approach (Tables 9 and 10), was taken into account in order to assess the efficiency of the bank. Based on this model results, in 2022, 6 out of 20 banks were fully efficient. Srpska bank was the least efficient in 2022. The efficiency scores for the output-oriented BCC model for 2022 were determined using this model (Table 9). Banks that, regardless of pure technical efficiency, are not efficient at the level: Addiko, Intesa, Postanska Stedionica, Erste, Eurobank Direktna, Alta, MiraBank, NLB Komercijalna banka OTP, and Raiffeisen bank. The banks that are technically efficient and functioning on the most suitable returns to scale are API, AIK, BOC, 3 Banka, Mobi, and Unicredit bank.

Based for the output-oriented CCR model, in 2023, 5 out of 20 banks were fully efficient. Srpska bank was the least efficient in 2023. The efficiency scores for the output-oriented BCC model for 2023 were determined using this model (Table 10). To facilitate comparison, the efficiency scores for the CCR and BCC models are shown. Banks that, regardless of purely technical efficiency, are not efficient at the level: AIK, Intesa, Postanska Stedionica, Erste, Eurobank Direktna, Adriatic bank, Alta, MiraBank, NLB Komercijalna banka, OTP, and Raiffeisen, bank. The banks that are technically efficient and functioning on the most suitable returns to scale are API, BOC, 3 Banka, Mobi, and Unicredit bank.

Table 9. DEA output-oriented CCR and BCC model, and Scale Efficiency results: Profitability Approach (in 2022)

DMU	Score CRS (Technical Efficiency)	Rank	Score VRS (Pure Technical Efficiency)	Rank	Scale Efficiency
API	1	1	1	1	1
ADDIKO	0.983	8	0.983	13	1
AIK	1	1	1	1	1
INTESA	0.697	12	1	1	0.697
BOC	1	1	1	1	1
POSTANSKA STEDIONICA	0.721	10	1	1	0.721
ERSTE	0.787	9	0.994	12	0.791
EUROBANK DIREKTNA	0.399	19	0.743	16	0.537
ADRIATIC BANK	0.605	14	0.643	18	0.940
HALK	0.549	16	0.685	17	0.801
ALTA	0.622	13	0.873	15	0.712
MIRABANK	0.999	7	1	1	0.999
NLB KOMERCIJALNA BANKA	0.584	15	0.922	14	0.632
OTP	0.519	17	1	1	0.519
3 BANKA	1	1	1	1	1
PROCREDIT	0.486	18	0.585	19	0.830
RAIFFEISEN	0.710	11	1	1	0.710
SRPSKA	0.290	20	0.292	20	0.991
MOBI	1	1	1	1	1
UNICREDIT	1	1	1	1	1
Mean	0.747		0.886		0.844

Source: Author's calculation

Table 10. DEA output-oriented CCR and BCC model, and Scale Efficiency results: Profitability Approach (in 2023)

DMU	Score CRS (Technical Efficiency)	Rank	Score VRS (Pure Technical Efficiency)	Rank	Scale Efficiency
API	1	1	1	1	1
ADDIKO	0.869	8	0.885	14	0.982
AIK	0.731	12	0.859	16	0.851
INTESA	0.704	13	1	1	0.704
BOC	1	1	1	1	1
POSTANSKA STEDIONICA	0.824	9	1	1	0.824
ERSTE	0.803	10	0.912	13	0.881
EUROBANK DIREKTNA	0.546	19	0.803	17	0.680
ADRIATIC BANK	0.968	6	1	1	0.968
HALK	0.551	18	0.660	18	0.835
ALTA	0.948	7	1	1	0.948
MIRABANK	0.582	16	1	1	0.582
NLB KOMERCIJALNA BANKA	0.695	14	0.877	15	0.792
OTP	0.631	15	1	1	0.631
3 BANKA	1	1	1	1	1
PROCREDIT	0.554	17	0.623	19	0.889
RAIFFEISEN	0.797	11	1	1	0.797
SRPSKA	0.352	20	0.365	20	0.964
MOBI	1	1	1	1	1
UNICREDIT	1	1	1	1	1
Mean	0.778		0.899		0.866

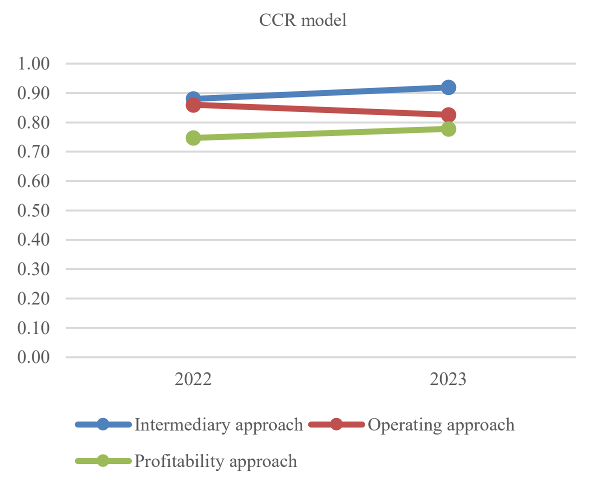
Source: Author's calculation

5. Discussion

Since the average efficiency scores for all applied approaches are higher than 0.83, the results of the used DEA CCR model demonstrate that the banking sector in Serbia functions at an exceptional level of efficiency. The profitability approach has the lowest average efficiency scores throughout the two years under observation, whereas the intermediary approach yields the highest efficiency scores (Figure 1). The profitability function comes in third, followed by the operating function and the intermediary function, in response to the study question of which bank function is the most efficient. These results demonstrate that there is room to improve the banking sector's profitability and cost-effectiveness.

These results are in line with the results of studies by other authors, who also state the intermediary approach, as the approach with the highest efficiency score, then operating, and finally the profitability approach (e.g. Marcikić Horvat et al., 2022a).

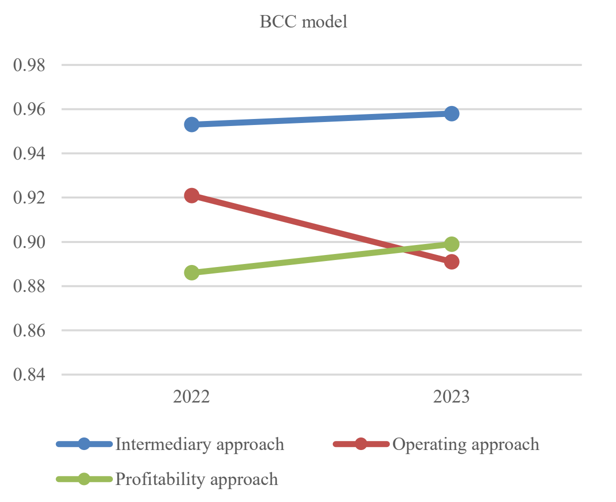
Figure 1. Average Efficiency Scores for CCR model



Source: Author's presentation

Although the average efficiency rating for all applied approaches is higher than that of the DEA CCR model, and amounts to slightly less than 0.92, the results of the DEA BCC model show similar results to the DEA CCR model. The intermediary approach has the highest average rating, followed by the operational approach, and the profitability approach has the lowest (Figure 2).

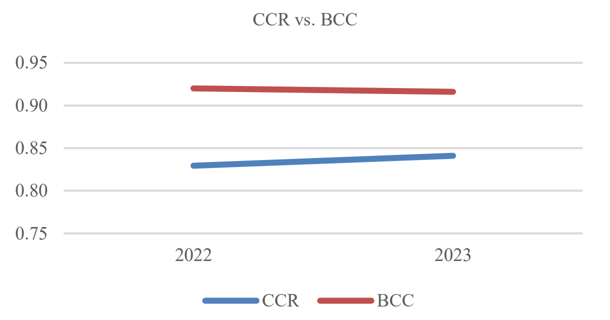
Figure 2. Average Efficiency Scores for BCC model



Source: Author's presentation

It is clear that the BCC results have superior efficiency when compared to constant returns to scale or the CCR model (Figure 3). Pai et al. (2020) point out that the BCC model has a convex line efficiency frontier, which reduces the distance to the efficiency frontier for the identified inefficient DMUs, whereas the CCR model has a straight line efficiency frontier. There is a reduced difference in efficiency between the BCC model and the CCR model because scale inefficiency is not considered (Cova-Alonso et al., 2021). The whole concept of technical efficiency is not the focus of the BCC model; rather, it only considers pure technical efficiency. Toloo and Nalchigar (2009) discuss the benefits of the BCC model over the fundamental CCR model and its applicability. The argument that the BCC model is superior is supported by an analysis of a case involving 19 facility plan choices. They emphasize that when returns to scale are variable, the BCC model works well. Pai et al. (2020) suggest using the BBC model to check how well service providers in both the public and private sectors are doing. On the other hand, Thagunna and Poudel (2013) point out that there is no significant difference between the results obtained using the CCR model and the results obtained using the BCC model.

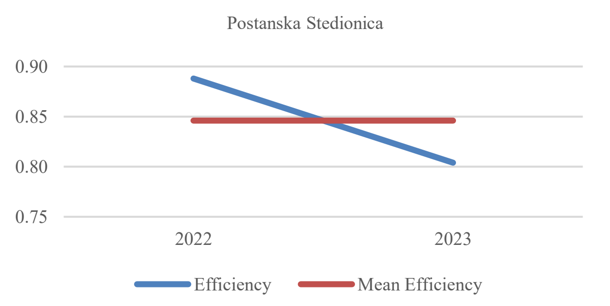
Figure 3. DEA CCR model vs. DEA BCC model



Source: Author's presentation

When conducting a thorough study of a single bank, DEA analysis is more beneficial as it provides the bank with enhanced insight into potential areas for efficiency improvements. For example, Postanska Stedionica Bank's efficiency is decreasing (Figure 4), and it needs to identify the reasons why in order to address the issue.

Figure 4. DEA Results for Postanska Stedionica Bank



Source: Author's presentation

With the current amount of inputs, Postanska Stedionica can boost its output by 20% even more efficiently, as indicated by its efficiency score of 80%. Postanska Stedionica has been compared to reference banks known as the benchmarks (Table 11). Table 11 presents the actual and projection values that would have resulted from an efficient operation of the bank. This bank might see a 23.07% drop in capital, a 14.12% increase in labor costs, an 86591635.17% increase in loans, and a 25620726.33%

increase in investment. Efficiency would rise with loan diversification or a decrease in bad loans.

Table 11. Actual and projection values for Postanska Stedionica Bank

Improvements	Deposits	Labor Cost	Capital	Loans	Investment
Actual	421902583	5680329.00	35005178.00	215993120	5843573
Projection	421902583	1851260467674	35005178	268556371975429	1497171689608
Change (in %)	0	14.12	-23.07	86591635.17	25620726.33

Source: Author's calculation

6. Conclusion

A more broadly applicable nonparametric approach for frontier-based linear programming optimization performance evaluation is data envelopment analysis. This approach is a non-parametric substitute for regression. The efficiency of the units cannot be suitably assessed by the econometric methodology if they contain many inputs and outputs. Analyzing a DMU with many inputs and numerous outputs in order to determine its efficiency score is the primary goal of data envelopment analysis. It is common practice to compare banking systems using the DEA approach. When assessing a bank's efficiency, the CCR and BBC models with CRS or VRS are frequently employed. This study compared the three widely utilized methods in order to determine which is the most effective. These methods are rarely employed in a comparison, as the literature study shown. The profitability strategy comes in third, operating approach is second, and intermediary approach is the most efficient of the three techniques under consideration. Every method examines the banks' efficiency from a distinct perspective. The BBC model outperformed the CCR model in assessing the effectiveness of banks.

Based on all three of the approaches taken into consideration and the two applicable models, Serbianbanking industry generally received good efficiency ratings during the observed time. Banks with fewer market shares and net balance sheet assets performed worse than larger banks. The huge volume of mergers and acquisitions in the preceding few years may have contributed to the reduced results, and in the upcoming years, M&A's synergistic benefits may be anticipated. From a practical standpoint, bank management can also benefit from the significance of the presented data. Decision-makers may find the bank efficiency findings helpful in identifying which institutions can raise their profits, expenses, or intermediary efficiency. When everything is taken into account, it can be said that various banks' profit efficiency management needs the greatest work. As a result, in order to raise profit levels, the banks with market share can acquire the smaller, less lucrative banks. This would increase the profitability of the banking industry. Also, for banks operating in Serbia, it is crucial to make adjustments to inputs and outputs: bank employees should be trained to reduce the amount of human input required for each output; deposits should be improved to increase desired outputs; and non-performing loans should be reduced by strengthening internal control over loan provision and improving loan quality.

Since the choice of variables and sample has a significant impact on the outcomes of DEA models, the technique used in this study is mostly responsible for its limitations. Since DEA measures efficiency relative to other units alone, it is a relative technique. Changes in the number of banks used in the analysis or in the selection of input or output variables would therefore undoubtedly affect the efficiency scores and outcomes. DEA does not have any predictive capabilities, and the selection of factors and DMUs continues to affect the outcome. Better results and further analyses that would be useful in figuring out how efficiency improved or decreased over time would come from accounting for a longer time period.

References

Ahn, H., Afsharian, M., Emrouznejad, A., & Banker, R. (2018). Recent developments on the use of DEA in the public sector. *Socio-Economic Planning Sciences*, *61*, 1-3. https://doi.org/10.1016/j.seps.2017.06.001

Amado, C.A.F., Santos, S.P., & Marques, P.M. (2012). Integrating the data envelopment analysis and the balanced scorecard approaches for enhanced performance assessment. *Omega*, *40*(3), 390-403. https://doi.org/10.1016/j.omega.2011.06.006

Banker, R.D., Amirteimoori, A., & Sinha, R.P. (2022). An integrated Data Envelopment Analysis and generalized additive model for assessing managerial ability with application to the insurance industry. *Decision Analytics Journal*, *4*, 100115. https://doi.org/10.1016/j.dajour.2022.100115

Banker, R.D., Charnes, A., & Cooper, W.W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science*, *30*(9), 1031-1142. https://doi.org/10.1287/mnsc.30.9.1078

Beccalli, E., Casu, B., & Girardone, C. (2006). Efficiency and stock performance in European banking, *Journal of Business Finance & Accounting*, *33*(1–2), 245–262. http://dx.doi.org/10.1111/j.1468-5957.2006.01362.x

Berger, A., & Humphrey, D. (1997). Efficiency of Financial Institutions: International Survey and Directions for Future Research. *European Journal of Operational Research*, *98*(2), 175-212. http://dx.doi.org/10.1016/S0377-2217(96)00342-6

Boďa, M., & Zimková, E. (2015). Efficiency in the Slovak banking industry: a comparison of three approaches. *Prague Economic Papers*, 2015(4), 434-451. https://doi.org/10.18267/j.pep.546

Charnes, A., Cooper, W.W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429-444. https://doi.org/10.1016/0377-2217(78)90138-8

Coelli, T., Rao, D.S., & Battese, G.E. (1998). *An introduction to efficiency and productivity analysis*. NY: Springer. http://dx.doi.org/10.1007/978-1-4615-5493-6

Cova-Alonso, D.J., Díaz-Hernández, J.J., & Martínez-Budría, E. (2021). A strong efficiency measure for CCR/BCC

models. *European Journal of Operational Research*, *291*(1), 284-295. https://doi.org/10.1016/j.ejor.2020.09.006
Emrouznejad, A., & Yang, G.-l. (2018). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio-Economic Planning Sciences*, *61*, 4-8. https://doi.org/10.1016/j.seps.2017.01.008
Eriņa, J., & Eriņš, I.(2013). Efficiency of the Latvian commercial banking system: a DEA model evaluation, In *18th International Scientific Conference "Economics and Management – 2013"*, 24–26 April 2013, Kaunas, Lithuania.
Fethi, M.D., & Pasiouras, F. (2010). Assessing bank efficiency and performance with operational research and artificial intelligence techniques: a survey, *European Journal of Operational Research*, *204*(2), 189-198. http://dx.doi.org/10.1016/j.ejor.2009.08.003
Heffernan, S. (2005). *Modern Banking*. Chichester: John Wiley & Sons, Ltd.
Lampe, H.W., & Hilgers, D. (2015). Trajectories of efficiency measurement: A bibliometric analysis of DEA and SFA. *European Journal of Operational Research*, *240*, 1–21. http://dx.doi.org/10.1016/j.ejor.2014.04.041
Lukić, R., Sokić, M., & Vojteski Kljenak, D. (2020). Analysis of insurance companies' efficiency in the Republic of Serbia. *Economic and Environmental Studies, 18*(45), 249–264. https://doi.org/10.25167/ees.2018.45.14
Marcikić Horvat, A., Milenković, N., Radovanov, B., Zelenović, V., & Milić, D. (2022a). DEA efficiency of Serbian banks-comparison of three approach. *Анали Економског факултета у Суботици – The Annals of the Faculty of Economics in Subotica*, *59*(50), 019-035. http://dx.doi.org/10.5937/AnEkSub2200011M
Marcikić Horvat A., Radovanov B., Milić D., & Milenković N. (2022b). Efficiency Analysis of Serbian Banking Sector Using Data Envelopment Analysis – Pre-pandemic era. *BizInfo (Blace)*, *13*(2), 41-47. https://doi.org/10.5937bizinfo/220201M
McAllister, P.H., & McMaus, D. (1993). Resolving the scale efficiency puzzle in banking. *Journal of Banking and Finance*, *17,* 389-405. http://dx.doi.org/10.1016/0378-4266(93)90039-G
Milenković, N., Radovanov, B., Kalaš, B., & Horvat, A.M. (2022). External Two Stage DEA Analysis of Bank Efficiency in West Balkan Countries. *Sustainability*, *14*(2), 978. https://doi.org/10.3390/su14020978
Nigmonov, A. (2010). Bank performance and efficiency in Uzbekistan. *Eurasian Journal of Business and Economics*, *3*(5), 1-25.
Nourani, M., Malim, N.A.K., & Mia, M.A. (2021). Revisiting efficiency of microfinance institutions (MFIs): an application of network data envelopment analysis. *Economic Research-Ekonomska Istraživanja, 34*(1), 1146-1169. https://doi.org/10.1080/1331677X.2020.1819853
Pai, P., Khan, B.M., & Kachwala, T. (2020). Data Envelopment Analysis - Is BCC model better than CCR model? Case of Indian Life Insurance companies. *NMIMS Management Review*, XXXVIII(1), 17-35.
Raj,K.K., Srinivasan, S., & Nandakumar, C.D. (2023). Efficiency analysis of reinsurers in India: a three stage fuzzy closed system DEA approach. *OPSEARCH*, *60*, 1179–1201. https://doi.org/10.1007/s12597-023-00651-2
Sealey, C.W., & Lindley, J.T. (1977). Inputs, outputs, and a theory of production and cost at depository financial institutions, *The Journal of Finance*, *32*(4), 1251–1266. http://dx.doi.org/10.1111/j.1540-6261.1977.tb03324.x
Shahooth, K., & Battall, A.H. (2006). Using data envelopment analysis to measure cost efficiency with an application on Islamic banks. *Scientific Journal of Administrative Development*, *4*, 134-156.
Singh, G., Singh, P., & Munisamy, S. (2008). A cross country comparison of banking efficiency: Asia Pacific banks. *International Review of Business Research Papers*, *4*(3), 73–95.
Thagunna, K.S., & Poudel, S. (2013). Measuring Bank Performance of Nepali Banks: A Data Envelopment Analysis (DEA) Perspective. *International Journal of Economics and Financial Issues*, 3(1), 54-65.
Titko, J., Stankevičienė, J., & Lāce, N. (2014). Measuring Bank Efficiency: DEA Application. *Technological and Economic Development of Economy*, *20*(4), 739-757. https://doi.org/10.3846/20294913.2014.984255
Toloo, M., & Nalchigar, S. (2009). A new integrated DEA model for finding most BCC-efficient DMU. *Applied Mathematical Modelling*, *33*(1), 597-604. https://doi.org/10.1016/j.apm.2008.02.001
Ullah, S., Majeed, A., & Popp, J. (2023). Determinants of bank's efficiency in an emerging economy: A data envelopment analysis approach. *PLoS ONE*, *18*(3), e0281663. https://doi.org/10.1371/journal.pone.0281663
Wang, K., Huang, W., Wu, J., & Liu, Y. N. (2014). Efficiency measures of the Chinese commercial banking system using an additive two-stage DEA. *Omega*, *44*, 5-20. https://doi.org/10.1016/j.omega.2013.09.005
Wheelock, D.C., & Wilson, P. (1995). Why do banks disappear: the determinants of bank failures and acquisitions, *The Review of Economics and Statistics*, *82*, 127-138. http://dx.doi.org/10.1162/0034
Yue, P. (1992). Data Envelopment Analysis and Commercial Bank Performance: A Primer with Missouri Banks. *Federal Reserve Bank of St. Louis Review*, *74*, 31-45.
Zhou, Z., Amowine, N., & Huang, D. (2018). Quantitative efficiency assessment based on the dynamic slack-based network data envelopment analysis for commercial banks in Ghana. *South African Journal of Economic and Management Sciences*, *21*(1), a1717. https://doi.org/10.4102/sajems.v21i1.1717