ANALYSIS OF THE EFFICIENCY OF BANKS IN BOSNIA AND HERZEGOVINA BASED ON DEA AND SFA METHODS

Slađana Paunović*, Dajana Kovačević**

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Abstract

This paper analyzes the efficiency of banks in Bosnia and Herzegovina in 2023 using Data Envelopment Analysis (DEA) and Stochastic Frontier methods (SFA). The aim of the research is to measure the efficiency of banks in generating income, using variables such as total assets, number of employees and operating expenses as inputs, and interest and non-interest income as outputs. The results show that both methods produce similar average efficiency indices throughout the observed period. However, the analysis of the ranks indicates inconsistency in the assessment of efficiency at the level of individual banks. This suggests that while these methods provide stable insights into the overall efficiency of the banking sector, they become inconsistent when applied to individual banks.

Keywords: Efficiency, Data Envelopment Analysis, Stochastic Frontier Analysis

JEL D24, G21, C67

1. Introduction

The role of banks in any economy can be considered crucial, as they serve as the main financial intermediaries between savers and investors. Efficient business operations enable accumulation of savings, which are then directed towards productive investments. This, in turn, positively impacts the stability of companies and the financial sector, and also encourages innovation and economic growth. Therefore, it is not surprising that a large number of studies in the field of banking focus precisely on measuring and comparing the performance of banks and identifying the key factors that influence their success.

The assessment of bank efficiency is an important issue for all stakeholders, as it informs whether existing banking resources are used effectively. The aim of measuring efficiency is to determine a reliable indicator of business performance in the market, or an indicator that could point to the possibilities of failure for a banking institution. The efficiency indicator can also assist in assessing the impact of changes in various market conditions and regulations on bank performance. Based on the calculated areas of inefficiency, each bank can prepare strategies to improve its position in the market. Additionally, efficiency indices can also serve regulatory bodies in assessing the health of individual banks, based on which they can respond in a timely manner to prevent systemic weaknesses.

Assessing banking efficiency is most often conducted using the traditional financial ratio analysis. Kumbirai & Webb (2010) argue that financial indicators allow us to identify the unique strengths and weaknesses of banks, which in turn inform us about the bank's profitability, liquidity, and credit quality. These indicators are popular for several reasons. They are easy to calculate and interpret and they allow for the comparison of banks using benchmark values or averages. It can be said that these indicators represent a valuable tool for interpreting financial statements, allowing analysts to carry out a certain degree of comparison between companies of different sizes and companies within the overall industry. On the other hand, numerous studies (Zhu, 2000; Ho & Zhu, 2004) argue that the usefulness of traditional financial indicators for assessing and predicting the efficiency of enterprises is inadequate due to the univariate nature of the relationship analysis. One indicator is not sufficient to capture acomplete picture of an organization's performance across the scope of its activities, and there is no single criterion for selecting an indicator that meets the needs of all stakeholders (Ho & Zhu, 2004). Research shows that financial indicators can be an appropriate method only when decision-making units manage one input to generate one output. One of the drawbacks is that they do not provide enough

* Faculty of Economics, University of East Sarajevo, Bosnia and Herzegovina, sladjana.paunovic@ekofis.ues.rs.ba
** Faculty of Economics, University of East Sarajevo, Bosnia and Herzegovina, dajana.kovacevic@ekofis.ues.rs.ba

information when considering the effects of economies of scale and assessing measures of overall efficiency.

In the last thirty years, we have witnessed the development of an alternative methods for measuring efficiency known as frontier analysis. These methods involve determining efficient boundaries and measuring organizational inefficiency as the distance of the organization from that boundary. In this way, organizations can determine their efficiency in relation to best practices while taking into account the prevailing market conditions. The most popular types of data analysis using boundary methods are Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) (Kumbhakar & Lovell, 2000; Cooper, Seiford, & Zhu, 2011). These two methods determine the efficiency boundary, but they are based on different assumptions. The aim of this paper is to highlight that the application of modern methods in assessing the efficiency of financial institutions can provide a better insight into their operations, as well as to conduct a comparative analysis of these methods to examine the consistency of the obtained efficiency indices.

In the works, the DEA method predominates due to the less rigorous assumptions on which it is based. Studies on the consistency of efficiency measurement include different approaches to measuring the efficiency of banks. Given that there is a possibility of analyzing different aspects of bank efficiency, in this paper we will focus on measuring the efficiency of banks in generating their income. Efficiency in revenue generation can be explained as the process of optimizing various operations within banks in order to maximize revenue while minimizing costs. This means that it enables banks to allocate resources effectively, resulting in better business results, greater customer satisfaction, and investments in new technologies, which contribute to revenue growth.

2. Theoretical background

2.1 Literature review

There has been a significant number of studies applying frontier analysis methods to assess the efficiency of banking institutions In the literature, the DEA approach is more prevalent because it relies on fewer strict assumptions There is a large number of studies that use one of the frontier analysis methods to assess efficiency in various organizations, and there is also a series of studies analyzing their consistency. For example, in a study measuring cost efficiency using samples from 270 Italian banks with SFA (Resti, 1997), the author noted similarities between both approaches, such as comparable values and a high positive correlation between efficiency scores and rankings. Sheldon (1994) reached different conclusions by assessing efficiency using SFA and DEA on a sample of 477 Swiss banks, but did not find a clear connection between the rankings.

Weill (2004) analyzed the efficiency of European banks in five countries using parametric and non-parametric methods. His results indicate that the methods of frontier analysis are consistent with traditional indicators of banking efficiency, while significant correlation in ranking existed only in one country. Fiorentino, Karmann and Koetter (2006) studied the cost efficiency of German banks using both approaches. They reached similar results to those of previous authors. The DEA efficiency scores give higher average ratings compared to the SFA method, and the bank rankings based on efficiency are more consistent in more homogeneous groups

Nguyen *et al.* (2016) studied the cost efficiency of 32 Vietnamese banks from 2000 to 2014 using a two-stage approach that includes SFA and DEA. The results show moderate to high agreement between the SFA and DEA methods in ranking bank efficiency, with the Spearman rank correlation coefficient being 0.54, which is statistically significant at the 1% level. Both methods identified similar banks in the highest and lowest quartiles of cost efficiency, indicating relative consistency in identifying the best and worst banks.

Thoraneenitiyan and Avkiran (2009) analyzed the efficiency of banking systems in East Asian countries after the financial crisis, using an integrated approach that combines both methods. The authors stated that both methods produce similar average levels of efficiency, but that they differ significantly in the range of results and the ranking of individual banks. They attributed greater sensitivity to extreme values and the influence of outliers to the DEA method, while SFA allows for better separation of inefficiency from random disturbances. They concluded that using both methods in combination provides a more comprehensive picture of efficiency, with the consistency between the methods not being high, but the results complementing each other.

Ruinan (2019) conducted a comparative analysis of the profit and cost efficiency of banks in the USA and Canada based on the SFA and DEA methods. According to the results of this study, a low correlation of the efficiency index was demonstrated, as well as their expected lower average values in the DEA method.

Nguyen, Vu, and Dinh (2019) analyzed the efficiency of 30 Vietnamese commercial banks from 2011 to 2015 using both methods. Although the results indicated a relatively high average level of efficiency for both models, a very low correlation was found between the results (only 19.9%), indicating significant differences in the ranking of banks. The authors further pointed out that the size of the bank, its age, and state ownership have a positive effect on efficiency, with state-owned banks achieving better results in both models.

Similarly, Sakouvogui (2020) conducted a comprehensive efficiency analysis of 650 US banks using DEA and SFA. His study suggested that the DEA method exhibits higher sensitivity in classification and higher volatility in ranking banks, which the author attributed to the lower robustness of the model in cases of heterogeneous samples. Although the aggregate trends in efficiency estimates were similar, the differences in ranking were significant. As a solution, the author suggested combining DEA with cluster analysis to obtain more stable results.

Dar, Mathur, and Mishra (2021) focused on the Indian banking sector from 2014 to 2020, specifically considering the so-called "bad outcomes" such as non-performing loans. Their analysis showed that the DEA method favors private banks, while the SFA results indicate smaller differences in efficiency between public and private institutions. Interestingly, public banks, which have traditionally been considered less efficient, showed improvements following the reform measures implemented in 2016. The authors concluded that including negative outputs in the analysis represents a significant step towards a more realistic assessment of efficiency and its impact on financial stability.

The application of the DEA method in assessing bank efficiency in the countries of the region is receiving increasing attention, given the possibility of this approach to measure how banks use their resources and generate income under complex and dynamic market conditions. Husejinović (2019) analyzed the efficiency of commercial banks in the Federation of Bosnia and Herzegovina using the DEA method, where the results indicated significant differences in efficiency among different financial institutions over that period. This work provides a good basis for understanding local specificities and challenges in assessing banking efficiency in BiH. Čivić (2022) investigated the application of the DEA method in analyzing the efficiency of the banking market in Bosnia and Herzegovina, especially in the context of the challenges brought by the COVID-19 pandemic. This research contributes to the understanding of how external crises can affect bank performance, with the DEA method demonstrating flexibility in adapting to different conditions. In Serbia, a significant contribution is made by the work of Marčićić Horvat *et al*. (2022), who compared three different approaches to the application of the DEA method to assess bank efficiency. They emphasize that, although the approaches differ in certain technical aspects, they all provide relevant insights into the performance of banks on the Serbian market. This study also pointed to the importance of choosing the appropriate DEA model depending on the specifics of the analyzed sample and the research objectives. In addition, within the region, some authors applied other multi-criteria decision-making methods for assessing banking efficiency, such as AHP, PROMETHEE. and ELECTRE, which complement the results of the DEA method and allow for a more comprehensive analysis of the complex factors affecting bank operations. The application of these methods is particularly useful in situations where qualitative aspects are also taken into account or when it is necessary to rank banks according to multiple criteria.

2.1.1. DEA models

The DEA model was first proposed by Charnes and colleagues (1978) as a mathematical technique for measuring the relative efficiency of decision-making units (DMU_s). The authors extended Farrell's concept of efficiency measurement with multiple inputs and a single output to the concept of multiple inputs and multiple outputs, using linear convex combinations to convert it into a single virtual input or output. In this way, the efficient frontier is determined, and the relative efficiency of each *DMU* is measured under constant returns to scale (*CRS*), with values ranging between 0 and 1.

It is necessary to assess the efficiency of n decision-making units: DMU_1, $DMU_{...}$, $DMU_n(j = 1,2,\dots,n)$. Each of the n decision-making units uses different amounts of m inputs: $X_1, X_2, ..., X_m$, $(i = 1,2,\dots,m)$ to produce s different outputs: $Y_1, Y_2, ..., Y_s$. The output-oriented model will look like (Charnes, Cooper, & Rhodes, 1978):

$$\min h_k = \sum_{r=1}^{s} v_i \cdot x_{ik}$$

$$\sum_{r=1}^{s} \mu_r \, y_{rk} = 1$$

$$\sum_{r=1}^{s} \mu_r \cdot y_{rj} - \sum_{i=1}^{m} v_i \cdot x_{ij} \leq 0 \quad j = 1,\dots,n$$

$$\mu_r, v_i \geq \varepsilon, r = 1,\dots,s, i = 1,\dots,m$$

DMU_k is considered efficient if there is no other decision-making unit from the observed set that can produce greater outputs with its optimal weight coefficients and inputs. When DMU_k has an efficiency index less than one, it is inefficient, and there must be at least one decision-making unit with an efficiency index equal to one. The objective function of the model is defined to maximize the virtual output of the *DMU*, while its virtual input is equal to one. If the value of the objective function of the observed *DMU* is less than one, then those DMU_s whose virtual output is equal to the virtual input are considered reference units. The value of the relative efficiency index less than 1 shows the level to which inputs need to be reduced or output increased to become efficient. The dual form of this model is known as the envelopment model, and it is as follows (Charnes, Cooper, & Rhodes, 1978):

$$max\, \varphi_k$$

$$x_k \geq \sum_{j=1}^{n} x_{ij} \, \lambda_j \quad (i = 1,2,\dots,m)$$

$$\sum_{j=1}^{n} y_{rj} \, \lambda_j \geq \varphi y_{rk} \quad (r = 1,2,\dots,s)$$

$$\lambda_j \geq 0 \quad (j = 1,2,\dots,n)$$

The objective function of this model maximizes ϕ_k, *i.e.*, it maximizes the value of the output that can be achieved with the existing level of inputs for the k-th*DMU*. The first constraint of this model limits the weighted combination of all inputs for all DMU_s to be at most equal to the output of DMU_k multiplied by its efficiency. Similarly, the second constraint ensures that the weighted average of all outputs for all DMU_s is at least equal to the output of the *DMU* being evaluated.

Banker, Charnes, and Cooper (1984) extended the *DEA* model with the aim of measuring pure technical efficiency. This extension ignores the impact of the scale of operations on the efficiency of decision-making units by comparing the k-th*DMU* only with units of similar scale of operations. The output-oriented model with variable returns to scale (*BCC* model) is as follows (Banker, Charnes & Cooper, 1984):

$$(\min)\, h_k = \sum_{r=1}^{s} v_i x_{ik} - w$$

$$\sum_{i=1}^{m} u_r y_{rk} = 1$$

$$\sum_{r=1}^{s} u_r \cdot y_{rj} - \sum v_i \cdot x_{ij} - w \leq 0$$

$$j = 1,.2,..,n$$

$$u_r, v_i \geq \varepsilon, r = 1,\dots,s, i = 1,2,\dots,m$$

Its dual form in canonical form is (Banker, Charnes & Cooper, 1984):

$$(\max)\theta_k$$
$$\sum_{j=1}^{n} \lambda_j \cdot x_{ij} - s_r^+ = x_{ik}, \quad r = 1, 2, \ldots, s$$
$$\theta_k \cdot y_r - \sum_{j=1}^{n} \lambda_j y_{ij} \leq 0, \quad i = 1,2,\ldots,m$$
$$\sum_{j=1}^{n} \lambda_j = 1$$
$$\lambda_j \geq 0; \quad r = 1,2,\ldots,s, \quad j = 1,2,\ldots,n,$$

The dual *BCC* model differs from the dual *CCR* model by the additional constraint that allows for variable returns to scale, as the reference set is formed as a convex combination of DMU_s with a positive λ_j value in the optimal solution. The hypothetical unit formed by this model and the decision-making unit being evaluated are, thanks to this constraint, of similar scale and similar input-output mix.

Unlike the *CCR* model, which measures overall technical efficiency, the *BCC* model has the ability to decompose overall technical efficiency into pure technical efficiency and scale efficiency. In this way, the *BCC* model is able to assess "pure" technical efficiency. For this reason, it can be better than the *CCR* model in providing recommendations to decision-makers, such as introducing certain measures to improve performance. Since the *CCR* model measures overall technical efficiency, and the *BCC* model only pure technical efficiency, scale efficiency can be obtained as the ratio of these two efficiency indices. Scale efficiency shows whether the decision-making unit operates with the optimal scale of operations.

2.1.1. Stochastic Frontier Analysis

SFA is an econometric method also used to assess efficiency, with the difference that it takes into account stochastic or random factors that are not under the control of the decision-making unit. The method was simultaneously proposed by Aigner *et al*. (1977) and Meeusen & van den Broeck (1977), and first applied in the banking sector by Ferrier & Lovell (1990). It differs from other methods in that it separates inefficiencies from random errors. While random errors typically follow a standard normal distribution, the inefficiency term usually follows a truncated or half-normal distribution because inefficiency must be non-negative.

The *SFA* method uses a stochastic production function that consists of two main parts: the deterministic part (which represents the efficiency of the organization) and the stochastic part (which accounts for uncertainty and the influence of uncertain factors) (Greene, 2008). Essentially, due to this, the *SFA* method is suitable for use in all sectors that are subject to uncertainty.

The Cobb-Douglas frontier equation is most commonly used:

$$y_i = x_i \beta + v - u_i,$$
$$\varepsilon_i = v_{it} - u_i, u_i \geq 0$$

where:

y_i - logarithmic output for unit i,
x_i - $(K+1)$ vector of inputs, with the first element being 1 and the remaining elements being the logarithmic quantities of inputs x_i,
β - $(K+1)$ vector of unknown parameters that need to be estimated,
ε_i - the stochastic noise that contains the mandatory error and a component that is specific to efficiency, denoted as $v_i - u_i$, where v_i represents the random component, and u_i is the component reflecting the inefficiency of the organization (Battese & Coelli, 1995),
u_i – a non-negative random variable associated with technical inefficiency.

Since technical efficiency represents the ratio of the observed output of the i-th unit of observation to the potential output defined by the frontier function for a given input vector, it can be defined as follows:

$$TE_i = \frac{y_i}{exp(x_i\beta)} = \frac{exp(x_i\beta - u_i)}{exp(x_i\beta)} = exp(-u_i)$$

In the *SFA* model, uncertainty v_i is assumed to follow a normal distribution, while the inefficiency component u_i has a positive distribution, as inefficiency cannot be negative. This model allows for the estimation of organizational efficiency while taking random factors into account (Aigner *et al*., 1977).

3. Specifications and data

This study evaluates the efficiency of 21 banks in Bosnia and Herzegovina in 2023. The Development Bank of the Federation of Bosnia and Herzegovina was excluded as it operates on different principles, in order to achieve a more homogeneous sample. The data were taken from the banks' financial statements, which were available on their websites.

The following variables were used as inputs: total assets of the banks, number of employees, and operating expenses. Operating expenses include employee costs, depreciation, and other operating costs. Interest income and non-interest income were selected as outputs. Interest income has historically dominated the revenue structure of the banks, while in recent years, the share of non-interest income has increased, showing that banks are successful in diversifying their income.

The choice of input and output variables in the analysis of bank efficiency is based on the theory of production and the concepts of technical and allocative efficiency, where efficiency is defined as the bank's ability to maximize the use of available resources for generating income (Farrell, 1957). Total assets, number of employees, and operating expenses represent key inputs, as they reflect capital, labor and operating costs, while interest income and non-interest income include traditional and alternative sources of income, which allows for a comprehensive assessment of efficiency (Halkos & Salamouris, 2004; Yeh, 1996). The selection of variables in this analysis is in line with the profitability approach, which is used to measure the efficiency of income generation in banks. This approach allows for an assessment of how efficiently a bank uses available resources to generate profit, which is crucial for banking institutions whose primary function is to generate income and value (Horvat *et al.*2022).

This choice of output variables enables a more comprehensive understanding of the overall profitability of banks, as it includes both traditional sources of income, such as interest income, as well as alternative sources of income, which have become increasingly important recently. The selected variables follow the model proposed by Halkos, George E. and Salamouris (2004), where input and output factors are carefully selected with the aim of accurately measuring the efficiency of banks in utilizing their resources and generating income. They point out that this combination of input and output parameters provides a balanced measurement of the relationship between resources and income. Also, Kumar and Gulati (2008) in the analysis of Indian commercial banks apply the same set of input and output variables using the DEA method, emphasizing that this combination most accurately reflects the operational efficiency of banks in conditions of market competition. The consistent application of this set of variables in relevant research confirms their theoretical and empirical justification as a reliable framework for assessing the operational efficiency of banks, thus justifying their choice in this paper.

Both models, *CCR* and *BCC*, as well as *SFA*, are used. Considering previous studies that use both methods to assess banking efficiency, the evaluation is carried out for only one year to determine different information provided by different frontier analysis methods, as well as to compare their correlation.

The following (Table 1) provides original data for selected input and output variables used in the DEA analysis, as well as descriptive statistics that provide insight into their basic characteristics. It is noticeable that the highest degree of variation is found in fee income, but generally, the range of variation is high, which supports the fact that all commercial banks with different operational levels are included in the sample.

Table 1. Original data and descriptive statistics of the selected input and output variables used in the DEA analysis

Banks	Total assets (BAM 000)	Number of emloyees	Operating costs (BAM 000)	Interest income (BAM 000)	Fee income (BAM 000)
Addiko Bank a.d. Banja Luka	1012725	365	32265	46601	22943
Addiko Bank d.d. Sarajevo	1118164	331	73204	38521	22689
ASA banka d.d. Sarajevo	3018211	41	64888	86398	39894
Atos bank a.d. Banja Luka	1213691	388	34560	51614	25263
Bosna bank International d.d. Sarajevo	1543943	422	30718	50114	21042
Banka poštanska štedionica a.d. Banja Luka	493117	153	13440	16521	5416
Intesa	2613788	603	61390	75616	39341
KIB banka	128572	83	4266	3510	4266
MF banka a.d. Banja Luka	785221	334	6156	51242	13398
Nasa banka a.d. Banja Luka	329053	204	7650	11094	7583
NLB banka a.d. Banja Luka	2039576	512	29640	70724	42082
NLB banka a.d. Sarajevo	1787729	478	44697	60442	35417
Nova banka a.d. Banja Luka	2871084	679	55100	105359	55283
Privredna banka d.d. Sarajevo	634332	196	14718	18204	11247
ProCredit bank d.d. Sarajevo	919779	203	22006	33355	9500
Raiffeisen bank d.d. Bosna i Hercegovina	5195381	1382	149176	174571	128135
Sparkasse bank d.d. Bosna i Hercegovina	2262755	504	56659	73277	42645
Unicredit bank a.d. Banja Luka	1275916	386	38397	54758	21504
UniCredit d.d.	7165850	1144	145659	218699	105443
Union banka d.d. Sarajevo	1113618	209	14690	21322	4099
Ziraatbank d.d.	1423500	347	38259	52448	18502
Mean	1854571.67	426.86	44644,67	62590,00	32175,81
Standard deviation	1673825	324,68	39625,49	51892,67	31843,5
Minimum	128572	41	4266	3510	4099
Maximum	7165850	1382	149176	218699	128135

Source: Authors' calculation

The high variability across all variables further emphasizes the heterogeneity of the sample, which includes banks with different operational scales and business models.

4. Results and Discussion

4.1 Results and Analysis

Table 2 presents the efficiency indices calculated using the DEA and SFA methods. Four DEA indices and two SFA indices were evaluated, where in the first, interest income was used as the output, and in the second, non-interest income was used. As expected, a higher number of efficient banks were found in the models assuming variable returns to scale. The efficiency indices calculated based on input-oriented models were, on average, lower, which suggests that banks were more efficient in minimizing input variables compared to maximizing output variables. These results are consistent with empirical studies and the fact that increasing bank outputs is influenced by numerous external factors and is achievable only with significant changes in their business strategies.

According to the results, it can be seen that large banks with assets of more than BAM 2 billion have higher efficiency indices, while the dispersion of efficiency indices is significantly higher for smaller banks, starting from those with very low operational efficiency. In the case of medium-sized banks (with assets ranging from BAM 500 million to 2 billion), they achieve an efficiency index above 0.7. It can be concluded that, on average, the efficiency indices in the observed sample were high, but there were significant differences in the performance of banks depending on their size.

Table 2. Efficiency Scores

Banks/ efficiency scores*	CCR-I	CCR-O	BCC-I	BCC-O	SFA -1	SFA - 2
Addiko Bank a.d. Banja Luka	1	1	1	1	0.91878	0.61681
Addiko Bank d.d. Sarajevo	0.8724	0.8724	0.8974	0.893	0.810928	0.651924
ASA banka d.d. Sarajevo	1	1	1	1	0.820506	1
Atos bank a.d. Banja Luka	0.9514	0.9514	0.9637	0.9624	0.877047	0.81269
Bosna bank International d.d. Sarajevo	0.7171	0.7171	0.7253	0.721	0.863483	1
Banka poštanska štedionica a.d. Banja Luka	0.6369	0.6369	0.8183	0.7403	0.867008	0.804259
Intesa	0.7491	0.7491	0.7515	0.7726	0.823388	0.72866
KIB banka	1	1	1	1	0.557075	0.190694
MF banka a.d. Banja Luka	1	1	1	1	0.907906	0.528666
Nasa banka a.d. Banja Luka	0.8579	0.8579	0.9011	0.9106	0.928985	0.788811
NLB banka a.d. Banja Luka	1	1	1	1	0.918861	1
NLB banka a.d. Sarajevo	0.8858	0.8858	0.8965	0.8936	0.939791	0.809943
Nova banka a.d. Banja Luka	0.9685	0.9685	1	1	0.93196	0.636191
Privredna banka d.d. Sarajevo	0.76	0.76	0.7975	0.7833	0.857642	1
ProCredit bank d.d. Sarajevo	0.7707	0.7707	0.8524	0.8177	0.928985	0.788811
Raiffeisen bank d.d. Bosna i Hercegovina	1	1	1	1	0.886342	0.88041
Sparkasse bank d.d. Bosna i Hercegovina	0.8982	0.8982	0.9046	0.9024	0.892163	0.414483
Unicredit bank a.d. Banja Luka	0.8869	0.8869	0.8923	0.8883	0.950657	0.869978
UniCredit d.d.	0.8517	0.8517	1	1	0.852488	0.591395
Union banka d.d. Sarajevo	0.4676	0.4676	0.658	0.5125	0.865468	0.79099
Ziraatbank d.d.	0.7862	0.7862	0.7911	0.8073	0.823838	0.704798

*CCR-I — Charnes, Cooper, and Rhodes model, input-oriented; CCR-O — Charnes, Cooper, and Rhodes model, output-oriented; BCC-I — Banker, Charnes, and Cooper model, input-oriented, accounting for variable returns to scale; BCC-O — Banker, Charnes, and Cooper model, output-oriented, accounting for variable returns to scale; SFA-1 — Stochastic Frontier Analysis model with interest income as the dependent variable; SFA-2 — Stochastic Frontier Analysis model with non-interest income as the dependent variable

Source: Authors' calculation

Table 3 shows the distribution of banks' efficiency according to different models. The percentage of banks with low efficiency, below 0.5, was small, except in the SFA - 2 model, which indicates a weaker efficiency of banks in generating income outside of interest income. A large dispersion was also observed for this efficiency index, which suggests that banks could improve their income through product diversification, trading in financial instruments and other activities, which would also increase efficiency. Such strategies would reduce banks' dependence on interest income and improve their competitive position on the market. The highest percentage of banks with high efficiency was recorded according to DEA models with variable returns to volume, which was expected because these models better take into account the specific characteristics of banks, such as scalability. Also, DEA models generally show higher levels of efficiency compared to both SFA models, indicating that SFA models tend to assign lower efficiency values due to the presence of random noise and specific factors that affect the estimation of banks' production functions.

Table 3. Distribution of bank efficiency by different evaluation methods

Efficiency Score	CRS		VRS		SFA - 1		SFA-2	
	No. Of Banks	% of banks	No. Of Banks	% of banks	No. Of Banks	% of banks	No. Of Banks	% of banks
<0.5	1	4.76	0	0	0	0	2	9.52
0.5-0,6	0	0	1	4.76	1	4.76	2	9.52
0.6-0,7	1	4.54	0	0	0	0	3	14.29
0.7-0,8	5	23.81	4	19.05	0	0	4	19.05
0.8-0,9	6	28.57	5	23.81	12	57.14	6	28.57
0.9-1,0	2	9.52	3	14.28	8	38.09	0	0
1	6	28.57	8	38.09	0	0	4	19.05

Source: Author's calculation

The descriptive statistics of the assessed efficiency indices (Table 4) indicate that the average efficiency of banks was similar between most models, with the BCC model yielding the highest average efficiency (0.90), while the SFA-2 model assigns the lowest average efficiency (0.73). According to this parameter, we can conclude that we got consistent results, because the differences in the average values between the other models were within a smaller range. Also, the SFA-2 model had the widest range of variation with a minimum value of 0.19 and the highest standard deviation (0.21), indicating a greater dispersion of efficiency compared to the other models.

Table 4. Descriptive statistics of the efficiency scores

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
CCR-I	21	0.47	1.00	0.86	0.14
CCR-O	21	0.47	1.00	0.86	0.14
BCC-I	21	0.66	1.00	0.90	0.10
BCC-O	21	0.51	1.00	0.89	0.13
SFA -1	21	0.56	0.95	0.87	0.08
SFA - 2	21	0.19	1.00	0.74	0.21

Source: Author's calculation

At the end of the analysis, the Spearman rank correlation was calculated to assess the consistency between the efficiency rankings obteined by DEA and SFA methods. The results showed the highest correlation coefficient of 0.18, which was not statistically significant, and a correlation of 0.26, also not statistically significant at the 0.01 level. These findingsalign with earlier studies such as Ferrier and Lovell (1990), who reported similarly low correlation coefficients. This low consistency reflects the fundamental differences between the two methods. DEA, as a non-parametric technique, is sensitive to outliers and sample heterogeneity, while SFA, a parametric approach, accounts for statistical noise but depends on functional form assumptions. Similar observations were made by Thoraneenitiyan and Avkiran (2009), who noted that DEA showed greater sensitivity to extreme values, whereas SFA better separated inefficiency from random disturbances. Moreover, studies by Nguyen, Vu, and Dinh (2019) and Sakouvogui (2020) confirm that rankings based on DEA and SFA can differ substantially, especially in heterogeneous banking samples, and that factors such as bank size, ownership, and market environment play a significant role in explaining efficiency variation.

These findings emphasize the need for caution when interpreting efficiency rankings based solely on one method. A combined or comparative approach, applying both DEA and SFA methods, can provide a more nuanced and reliable assessment of bank efficiency, especially in complex markets like Bosnia and Herzegovina, as also suggested by Husejinović (2019) and Čivić (2022).

When interpreting the results of this research, it is necessary to keep in mind certain limitations that may affect the conclusions. Although almost all banks in Bosnia and Herzegovina are included in the analysis, their total number is relatively small, which may limit the statistical power and generalization of the findings. In addition, macroeconomic factors not considered in detail may have influenced the efficiency results and contributed to the differences between DEA and SFA methods. Nevertheless, this study provides important insights into the comparative characteristics of these methods and highlights the need for a careful approach when choosing an appropriate method for efficacy analysis.

5. Conclusion

This paper analyzes the efficiency of banks in generating revenue in Bosnia and Herzegovina during 2023. We used the DEA and SFA methods. The results show that larger banks are more efficient than the smaller ones. The differences are particularly evident in banks with assets of less than BAM 2 billion. Banks are better at reducing costs than at increasing revenue, which is expected. The DEA method shows that banks receive higher scores in models that account for variable returns to scale, meaning that models considering changes in returns as the scale operations increases or decreases tend to provide favorable efficiency assessments. The analysis using the SFA method indicates a greater variation in efficiency among banks, particularly in relation to non-interest income. This suggests that banks face challenges in diversifying their income. Overall, we can say that banks in Bosnia and Herzegovina could be more efficient. This can be achieved by better resource utilization, greater income diversification, and adapting strategies to the market. Further research could examine long-term trends and strategies for improving the performance of the banking sector.

A comparative analysis of bank efficiency using DEA and SFA methods highlights the complexity and challenges in accurately measuring performance in the banking sector. Although both methods aim to estimate the efficiency frontier, fundamental differences in their assumptions lead to different results, especially in terms of ranking individual banks. These inconsistencies indicate that relying on only one method can lead to erroneous conclusions about relative efficiency. In contrast, the application of a comparative approach provides a broader and more balanced picture, especially when assessing banks in heterogeneous and dynamic environments.

Given the limited correlation between the results of DEA and SFA methods, future research could be directed towards developing integrated models that combine the advantages of both approaches. In addition, it is desirable to include macroeconomic and institutional factors as additional variables that may affect efficiency, as well as to examine the sensitivity of the results to the choice of input and output variables.

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