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ORIGINAL SCIENTIFIC PAPER

Tailoring the DEA Framework for Emerging Markets: Evidence from the Banking Sectors of Serbia and Montenegro

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ABSTRACT
The aim of this research is to analyze the relative efficiency and productivity changes of the banking sectors in the Republic of Serbia and Montenegro in the period from 2010 to 2024, using the non-parametric DEA (Data Envelopment Analysis) method on unbalanced panel data. Given the fundamental differences between these two markets, the research applies methodologically adapted specifications: the profitability approach for Montenegro and the intermediary approach for Serbia. The basic results of the BCC DEA model are additionally deepened by the super-efficiency model for more precise ranking, as well as by the Malmquist index to monitor productivity dynamics over time. The results indicate that in Montenegro, most banks record high technical efficiency in capital management, but this apparent success masks serious structural problems, given that a significant number of banks recorded a regression in overall productivity (Malmquist index < 1). On the other hand, the Serbian market records stable productivity growth in more than 85% of the banks in the sample, with the largest systemic banks continuously dominating. It is concluded that the selection of inputs and outputs must be market-driven, highlighting that a customized methodological framework is essential to adequately address the structural specificities and operational differences within the sectors.

Keywords: *efficiency, DEA method, Super-efficiency, Malmquist index, banking sector, Serbia, Montenegro*

JEL Classification: G21, L1

INTRODUCTION

Most post-transition countries in SEE have financial systems strongly influenced by the banking sector due to insufficient development of financial markets. As a result, the banking system has a significant impact on economic growth and development in these countries, and the analysis of the profitability and efficiency of the banking sector provides important information for both potential investors and economic policymakers. Regulators and market participants in general were faced with numerous challenges in the period following the last global financial crisis, so they had to react appropriately and strengthen the banking sector's resilience to unexpected events in the subsequent period (Mirković, Matić & Dudić, 2024). Additionally, in the case of Montenegro, we should not lose sight of the fact that the Central Bank of Montenegro also has a limited range of monetary policy instruments at its disposal, imposed by the euroisation regime (Žugić & Fabris, 2014).

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In earlier research, financial indicators were mainly used as efficiency indicators, such as ROA (Return on Assets), ROE (Return on Equity), CIR (Cost to Income Ratio), and Net Interest Margin. In recent research, efficiency is predominantly examined through parametric and non-parametric methods.

Parametric methods start from the assumption of a certain functional form of the relationship between input and output, and the most commonly used methods are Stochastic Frontier Analysis (SFA), developed by Aigner, Lovell & Schmidt (1977), then Distribution Free Approach (DFA), which provides the possibility of using panel data and Thick Frontier Approach (TFA). Non-parametric methods do not require an assumption about the functional form of the connection between input and output, and the DEA (Data Envelopment Analysis) method is most often used. In academic research, there are also papers that analyze the efficiency results obtained through a combination of several methods.

DEA analysis is used in the banking sector to assess bank efficiency in terms of how the use of available resources (inputs) generates results (outputs). DEA is a non-linear mathematical model that, in the broadest sense, can identify the most efficient and inefficient banks, suggest whether there is an excess of inputs or a deficit of outputs, assess scalability, and consequently serve as a very helpful tool in the strategic planning, resource optimization and performance management of the banking sector.

The most commonly used DEA models in academic research are the CCR model (Charnes, Cooper & Rhodes, 1978), which assumes constant returns to scale and measures total technical efficiency and the BCC model (Banker, Charnes & Cooper, 1984), which assumes variable returns to scale and measures pure technical efficiency (Othman, Mohd-Zamil, Rasid, Vakilbashi & Mokhber, 2016). Then there is the Super-efficiency model (Andersen & Petersen, 1993), which ranks efficient banks (after eliminating the most efficient bank from the set), as well as the Malmquist index (Färe, Grosskopf, Norris, & Zhang, 1994), which enables the analysis of productivity over time.

To provide a clearer analytical framework and address the specific dynamics of these emerging markets, this study focuses on answering the following research questions:

- How do the levels of relative efficiency and productivity dynamics differ between the banking sectors of Serbia and Montenegro over the 2010–2024 period?
- To what extent do methodological specifications (profitability vs. intermediary approach) affect the robustness of efficiency assessments in these two markets?

Throughout this paper, *efficiency* refers to technical efficiency from the BCC model, *productivity* refers to Malmquist index changes over time, and *performance* is used as a general term for overall bank outcomes.

The structure of the paper is as follows. In the subsequent section, we present a literature review of banks' efficiency and productivity. This is followed by the Methodology, then the Results of the efficiency of the banking sector of the Republic of Serbia and Montenegro and finally the Conclusion.

LITERATURE REVIEW

The first book that presented in detail the application of the DEA model in banking and other financial services was Data Envelopment Analysis in the Financial Services Industry (Paradi, Sherman & Tam, 2018).

An important question that arises during DEA analysis is which indicators should be used as inputs and outputs. Three dominant approaches to defining inputs and outputs in the analysis of the banking sector using DEA methods are defined in the literature. The first is the production approach, in which banks are viewed as producers of products and services, while labor and other resources are most often used as inputs, and deposits, loans and other services that can be expressed in value or in the number of transactions are treated as outputs. The second is the intermediary approach that analyzes how efficiently banks collect deposits from clients, and subsequently invest those funds, where the inputs are deposits and other funds collected from clients, while the outputs are investments in the form of loans, mortgages and other assets. Third is the profitability approach, which examines how a bank uses its inputs, such as costs, to achieve outputs in the form of income (Maradin, Draženović & Benković, 2018).

The first approach is most often used in the analysis of the efficiency of individual branches within a particular bank, while the second and third approaches are used when comparing different banks within a market or across countries. As Enguene (2025) pointed out the choice of inputs and outputs in banking-sector productivity analysis is most often based on previous studies and is further complicated by the number of observations.

Tuškan & Stojanović (2016) analyzed and compared the efficiency of the banking sector across 28 European banking systems from 2008 to 2012. Efficiency was analyzed in two ways: first, through financial indicators such as ROA, ROE and CIR, and then by the DEA method, where the inputs are interest expenses and total operating expenses, and the outputs are interest income and total operating income, where the CCR DEA model, BCC DEA model and window analysis DEA technique were used. A comparative analysis of the results obtained through these two approaches suggests that the DEA methodology is useful in detecting early signs of inadequate business strategies that may lead to lower efficiency, particularly during periods of financial or macroeconomic instability. In addition, the results of both approaches indicate that banking systems in post-transition countries exhibit higher cost efficiency, are financed predominantly by long-term deposits, and generate higher income due to the specific competitive, financial, and macroeconomic environment, which increases risk and consequently the price of financial services (margins).

Tekić, Novaković & Milić (2018) evaluated the efficiency of 26 banks in the Republic of Serbia in 2018 using the DEA method. As inputs, they used total assets, total capital, and number of employees, while the outputs were the net business income and net profit of individual banks. The analysis showed that in 2018, out of 26 banks, only 10 banks operated efficiently, and that, in order to increase efficiency, non-efficient banks should increase the value of their assets, the value of total capital and the number of employees to be in the group of efficient banks operating in the Republic of Serbia.

The paper by Laporšek, Trunk & Stubelj (2022) analyzes changes in the productivity of a balanced panel of 1,915 European banks during the period 2013–2018. The paper uses the non-parametric DEA approach and the Malmquist Productivity Index (MPI). MPI estimates show a symbolic increase in bank productivity in half of the EU countries, while MPI decomposition indicates that productivity growth is mainly the result of technological improvement, which was particularly high among the new EU member states, alongside a significant decline in technical efficiency. The authors recommend that European banks further develop their business models in order to rationalize costs and increase operational efficiency, as well as encourage the adoption of fintech solutions and technological development to increase their productivity.

In the work of Milenković, Radovanov, Kalash & Horvat (2022), the sustainability of the intermediary role of banks was analyzed using the DEA model during the period from 2015 to 2019 in the Western Balkan countries, bearing in mind that interest rates were low during that period. The results suggest differences in the efficiency levels of banks, both within and across countries. Given that the results suggest a significant and positive relationship between bank size and relative efficiency, the expected trend is the continued takeover of small banks by large ones in these markets.

There is a lot of research that analyzes the issue of efficiency and productivity of the banking sector, but only few of them deal with the region of Southeast Europe in the period after 2010, and especially in the pandemic period, which was the motive to conduct research on a sample of the

Montenegrin and Serbian banking sector in the period from 2010 to 2024 to fill the gap in the literature.

METHODOLOGY

The very first article on DEA was published in 1978 by Charnes et al. DEA is a non-parametric method for measuring the productive efficiency of decision-making units (DMUs) (Krmac & Mansouri Kaleibar, 2023). The approach applies linear programming methods to transform inputs into outputs to assess the efficiency of similar organizations. The aim of this research is to analyze the relative efficiency of the banking sectors in the Republic of Serbia and Montenegro using the non-parametric DEA method. Both studies cover the period from 2010 to 2024 on a sample of 31 and 15 DMU (Decision-Making-Units) for Serbia and Montenegro, respectively. Data were taken from the official financial reports – balance sheet and income statement published by the National Bank of Serbia and the Central Bank of Montenegro. Given the extensive 15-year observation period, during which certain banks entered or exited the markets, this study employs an unbalanced panel data approach for both the Serbian and Montenegrin banking sectors. This allows the inclusion of all active banks in the specific years they operated, thereby preventing survivorship bias and reflecting the true market dynamics.

In this research, a direct comparative analysis of the banking sectors of Serbia and Montenegro using a single DEA model was not conducted due to the fundamental structural, monetary, and macroeconomic differences between these two markets. Given the specificities of the operating environments, it was necessary to apply different input and output specifications to obtain unbiased and relevant efficiency frontiers. Several key factors justify this methodological approach.

Firstly, Montenegro implements the euroization system, while the Republic of Serbia has its own currency; that is, the National Bank of Serbia has a greater number of instruments of the monetary policy at its disposal. Secondly, banking sectors differ significantly in terms of size and level of concentration. The Serbian banking sector is larger and more numerous, while the Montenegrin market is smaller and fragmented, with a smaller client base and lower volume of available deposits limiting traditional financial intermediation. Thirdly, there is a significant difference in economic structure, which directly affects banking operations. The credit portfolio of banks in Montenegro is strongly influenced by the high concentration of the economy in the tourism and services sectors, which makes it highly seasonal and susceptible to external shocks. In Serbia, the economic base is significantly more diversified, enabling banks to pursue a more stable and predictable policy of term transformation of funds. Differences in market structure further justify the application of a specific methodological approach. Namely, the banking sector in Serbia is fragmented, with a large number of banks holding individually small market shares, while the Montenegrin market is characterized by a higher level of concentration and an oligopolistic structure (Kaličanin & Terzić, 2023), which can directly influence non-linearity in achieving efficiency.

Based on a comprehensive literature review, a differentiated approach was applied in the selection of variables. Consequently, the profitability approach was implemented for Montenegro, while the intermediation approach was implemented for the Serbian market, as these methods best incorporate market specificities and reflect the operational realities of each banking sector. It is important to emphasize that the efficiency scores obtained for Serbia (using the intermediary approach) and Montenegro (using the profitability approach) are not directly comparable numerically, as they are derived from different input-output spaces. The cross-country analysis in this study is therefore conducted at the level of comparative patterns, trends, and structural insights – such as the proportion of banks demonstrating productivity growth, the stability of efficiency over time, and the relationship between technical efficiency and the Malmquist index.

This approach respects the fundamental structural differences between the two markets while still enabling meaningful cross-country inference.

RESULTS AND DISCUSSION

The following section details the results of the research. It begins with an evaluation of the banking sector in the Republic of Serbia, followed by an analysis of the results for the banking sector of Montenegro.

In the preliminary phase of the research, a correlation matrix analysis was conducted in order to identify the degree of correlation between the input variables. This analysis aimed to determine the potential multicollinearity between the proposed input variables and to enable the optimization of the model specification. Correlation analysis showed significant differences in mutual relationships between potential input variables, with correlation coefficients ranging from 0.583 to 0.987.

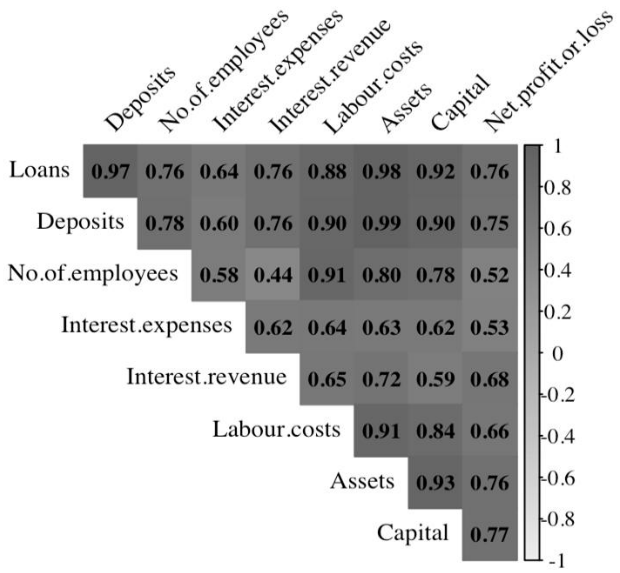

Figure 1. The correlation matrix

Source: Authors' calculations using the R programming language

In accordance with the recommendations from the literature (Dyson, Allen, Camanho, Podinovski, Sarrico & Shale, 2001; Nataraja & Johnson, 2011; Hair, Black, Babin & Anderson, 2010), a value of 0.80 was used as the upper limit of acceptable correlation. Figure 1 shows pairwise correlations among all potential input variables for Serbia. Coefficients above 0.8 (e.g., assets vs. deposits, capital vs. assets) indicate multicollinearity, which is why those variable pairs were never used together in the same model. The inputs retained in Models 2A–2C and 3A–3C all have correlations below 0.8, as shown in the lower left of the matrix. The full correlation matrix among all potential input variables (Figure 1) showed coefficients ranging from 0.583 to 0.987, with several pairs exceeding the 0.8 threshold (e.g., assets with deposits, capital with assets). However, for each of the six models defined in Table 1, we selected only input combinations where all pairwise correlations are below 0.8. For example, in models 2A–2C (capital, number of employees, interest expenses), the pairwise correlations are 0.72, 0.58, and 0.51; in models 3A–3C (deposits, number of employees, interest expenses), they are 0.72, 0.68, and 0.51. All these values are within the acceptable limit of 0.8. Therefore, multicollinearity is not a concern for any of the chosen specifications. It is important to clarify that correlation analysis was used exclusively as an initial screening tool to detect multicollinearity among input variables, following standard recommendations (Dyson et al., 2001; Hair et al., 2010). It was not intended to address monotonicity or to validate that variables reflect the production process. Regarding monotonicity (the requirement that increasing inputs should not decrease outputs), we note that all pairwise correlations between inputs and the output (loans) were positive (deposits–loans: 0.87; employees–loans: 0.76; interest expenses–loans: 0.81), which is consistent with the monotonicity condition.

Based on the results of the correlation analysis, where optimal combinations of variables with a moderate level of correlation were identified, six DEA models were defined and are shown in Table 1.

The comparative analysis of all six models was carried out through the evaluation of multiple performance metrics, which included the rate of outliers, stability of results, standard deviation and overall performance score. The results of the comparative analysis identified Model 3A as the optimal specification, achieving the highest overall performance score of 177.63 points.

Table 1. Specification of models: The list of inputs and outputs

Models	Inputs			Outputs
Model 2A	Capital	No. of employees	Interest expenses	Loans
Model 2B				Interest revenue
Model 2C				Net profit or loss
Model 3A	Deposits	No. of employees	Interest expenses	Loans
Model 3B				Interest revenue
Model 3C				Net profit or loss

Source: Authors

Overall scores are shown in Figure 2. As credit risk represents the most significant risk in the banking portfolio, and adequate management of this risk is directly reflected in the business results of banks (Radojević, Kesić, Rajin & Butėnas, 2023), Model 3A, which considers loans as a key output, is not only statistically the most reliable but also economically. So, beyond its statistical superiority, the selection of Model 3A as the primary specification for Serbia is grounded in the economic structure of the Serbian banking sector, which is described below. Serbian banks operate predominantly as traditional financial intermediaries: deposits consistently account for over 70% of total liabilities, and loans represent the main source of interest income. Deposits are therefore specified as the key input, capturing funding mobilization. The number of employees is included because Serbian banking remains branch-intensive, with labor as a major operational cost. Interest expenses reflect funding efficiency, which is critical given active monetary policy and interest rate fluctuations. Loans are specified as the output instead of interest revenue or net profit because loan volume directly measures intermediation activity, is less volatile, and is not distorted by pricing power or one-off items. To compare the six models, we computed three performance criteria: outlier resistance (100 minus the outlier rate in percent), stability (the percentage of banks classified as stable over time based on the Malmquist trend analysis), and the inverse of the standard deviation of efficiency scores (1/SD). Each criterion was normalized to a 0–100 scale across the six models using min-max normalization, where the best-performing model on each criterion received 100 points and the worst received 0 points. We then assigned weights a priori based on the relative importance of each criterion for reliability in DEA model selection: outlier resistance (40%), stability (35%), and inverse standard deviation (25%). The overall performance score for each model was calculated as the weighted sum of the three normalized criteria. Model 3A achieved the highest overall score (177.63), driven by its lowest outlier rate (1.1%), highest stability (82.9%), and lowest standard deviation (0.417). Therefore, Model 3A was selected as the primary specification for the Serbian banking sector.

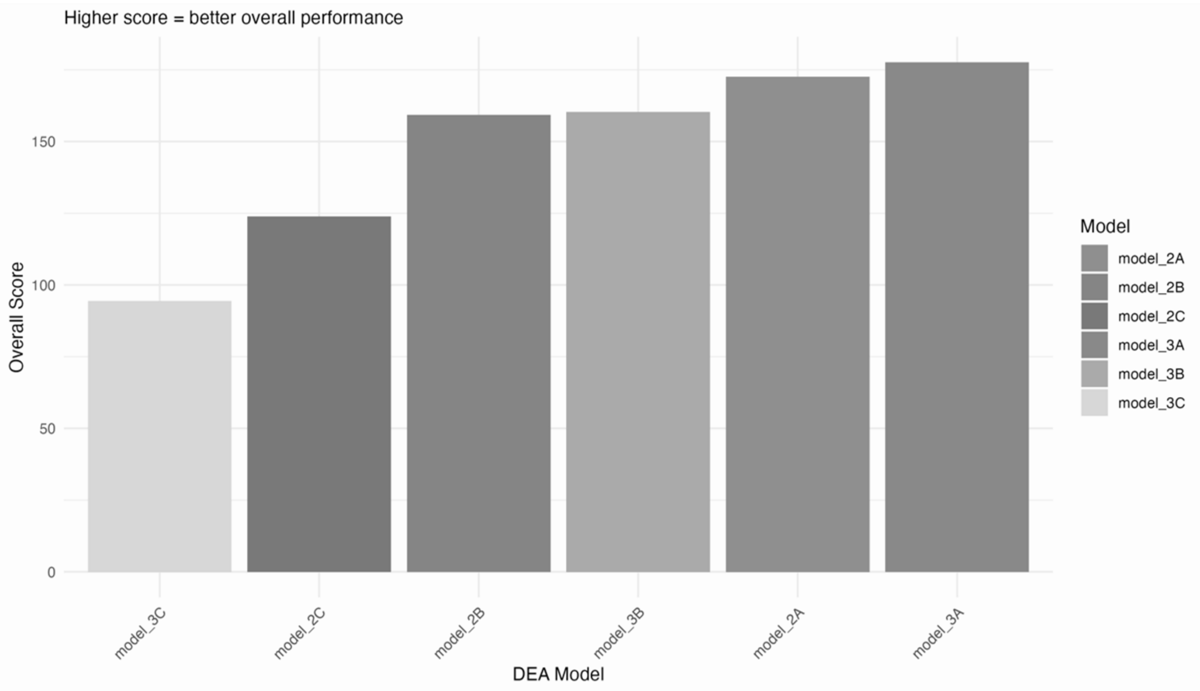

Figure 2. Model comparison: Overall scores, 2010-2024

Source: Authors' calculations using the R programming language

The superiority of Model 3A is reflected in two dimensions: 1) loans as an output variable proved to be the most stable indicator of banking activity, providing more consistent results compared to interest income and especially net profit, which showed the highest volatility (rate outlier 7.3-12.5%) and 2) the use of deposits as an input better reflects the traditional banking business model in relation to capital, which resulted in improved stability and reduced variability. This evaluation enabled the decision to use Model 3A as the primary specification for all subsequent research phases.

In order to ensure robust results, a comprehensive analysis of potential outlier observations was carried out through the application of the multiple detection method. The statistical analyses indicated certain deviations among individual banks, so Universal Bank was excluded because it went bankrupt in 2014 and because preliminary DEA runs indicated that its extreme values distorted the efficiency frontier.

The research used the input-oriented BCC model (Banker, Charnes & Cooper, 1984) with variable returns to scale (VRS), which represents the optimal choice for analyzing the efficiency of the banking sector. The choice of the BCC model instead of the CCR (constant returns to scale) is based on the following reasons: the banking sector is characterized by heterogeneity in business, where banks of different sizes operate under different conditions, the model takes into account the specifics of banking operations and their size, where smaller banks can also be efficient and enables decomposition into pure technical efficiency and efficiency of scale. Figure 3 shows average efficiency values according to the BCC model, using model 3A, for the period 2010-2024.

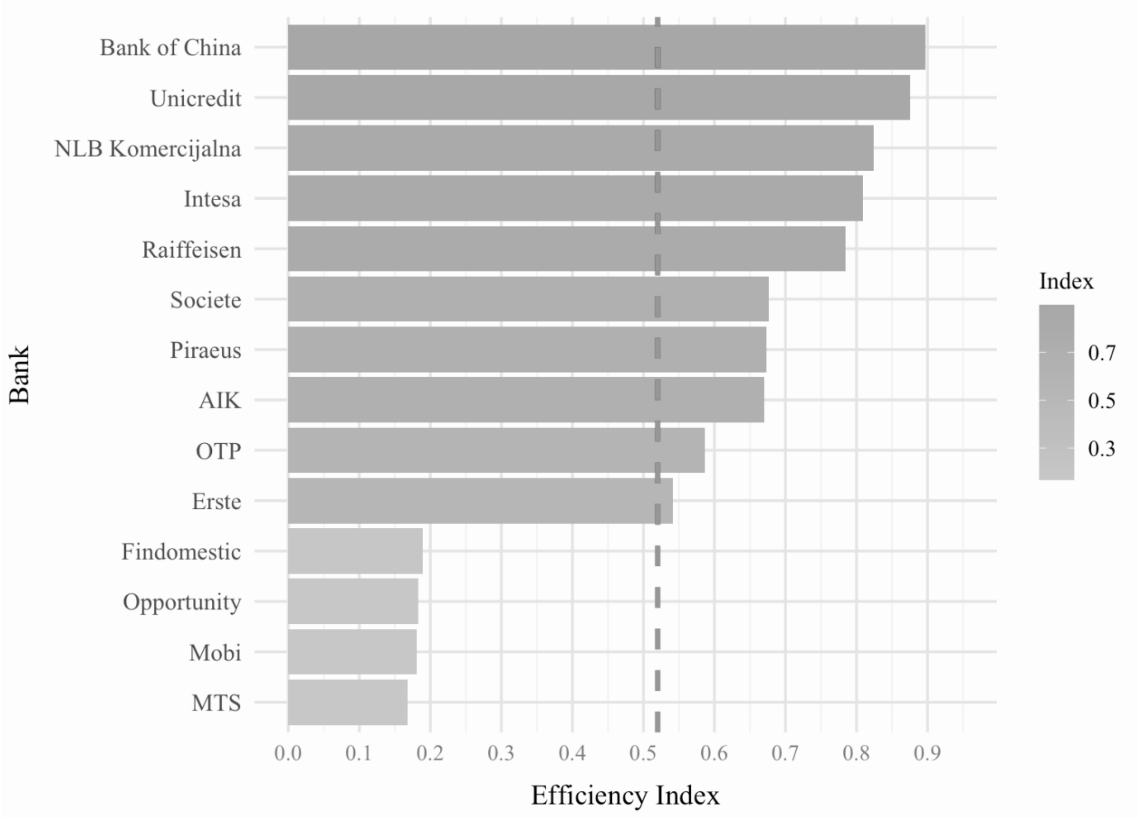

Figure 3. Average efficiency, selected banks, 2010-2024

Source: Authors' calculations using the R programming language

The results of the DEA analysis for Model 3A revealed significant heterogeneity in efficiency levels among the banks in the sample. Efficiency varied widely from 0.168 to 0.897, indicating substantial differences in the operational efficiency of the banking sector. The analysis identified a clear hierarchy of efficiency that can be categorized into four groups: 1) highly efficient banks (efficiency > 0.8), such as the Bank of China (0.897), Unicredit (0.875), NLB Komercijalna (0.824) and Intesa (0.809); 2) medium efficient banks (efficiency 0.6-0.8) such as Raiffaisen (0.784), Piraeus (0.673), AIK (0.670) and Societe (0.676); 3) low efficient banks (efficiency 0.3-0.6) such as OTP (0.586) and Erste (0.542); and 4) critically inefficient banks (efficiency<0.3): Findomestic (0.189), Mobi (0.181), Opportunity (0.183) and MTS (0.168). These threshold values (e.g., >0.8, 0.6–0.8) were chosen for descriptive purposes based on natural breaks in the distribution of efficiency scores. They are not derived from a statistical test and should be interpreted as relative within-sample categories rather than absolute benchmarks.

The average efficiency of the entire sample was 0.528, indicating significant scope for improving operational efficiency in the banking sector. These results clearly indicate the value of applying the BCC model to the analysis of banking operations and provide a solid basis for identifying best practice benchmarks.

The Bank of China entered the market in 2017 to support the financing of large international and infrastructure projects. Unlike other banks, it does not maintain a branch network for retail banking operations and does not rely on the collection of citizens' deposits. In the context of the applied DEA model, this structure of the balance sheet - where inputs such as the number of employees and the level of deposits are extremely low, while the volume of corporate loans placed is disproportionately high - leads the model to mathematically recognize this bank as highly efficient. The high average efficiency of the Bank of China should be interpreted with caution because it primarily reflects the specificity of its market niche rather than the conventional efficiency of financial intermediation that characterizes the rest of the sample. This case highlights a general limitation of DEA when the sample includes DMUs with fundamentally different business models: the efficiency frontier may be defined by an atypical unit, making scores for traditional banks less comparable. Researchers should therefore carefully consider whether to exclude such outliers or treat them separately. In our study, we retained the Bank of China but caution against interpreting its efficiency as superior performance in traditional intermediation.

After the initial DEA analysis, the research was expanded by applying two techniques in order to provide a deeper insight into the performance of the banking sector. Both methods, super-efficiency analysis and Malmquist index, contributed to a better understanding of both current efficiency and productivity dynamics during the observed period.

Super-efficiency analysis was applied to overcome the limitation of the standard DEA method in ranking units located on the efficiency frontier. This approach enabled a more precise identification and comparison between efficient banks. The Bank of China and Bank Intesa achieved infinite super-efficiency, which indicates their dominance and positioning as reference units for other banks in the sample. Infinite super-efficiency scores occur in the Andersen & Petersen (1993) model when a DMU, after being removed from the reference set, cannot be expressed as a linear combination of the remaining DMUs. This typically occurs in banks with extreme or unique input-output combinations. In our sample, the Bank of China's atypical business model (no retail branches, very low deposits and employees, yet large corporate loans) makes it a unique outlier. Banca Intesa, as a dominant systemic bank, serves as a unique benchmark that other banks cannot replicate when it is removed. Infinite scores do not imply infinite superiority – they simply indicate that these banks are exceptional cases not directly comparable to others using the super-efficiency model. For practical interpretation, all banks with infinite scores can be considered top-tier, but further ranking among them is not possible with this method. Unicredit then stood out as a highly ranked bank with a final super-efficiency value of 0.964, while Raiffeisen (0.801) and NLB Komercijalna (0.824) also showed a high degree of consistent efficiency. Additionally, analysis of the standard deviation of super-efficiency indicated significant differences in performance stability among banks. Banks such as NLB Komercijalna, with a very low standard deviation of 0.008, and Mirabank (0.072), indicate the stability of their performance. In contrast to these banks, Jugobank exhibited high volatility, with a standard deviation of 0.748, indicating fluctuations in its efficiency during the observed period.

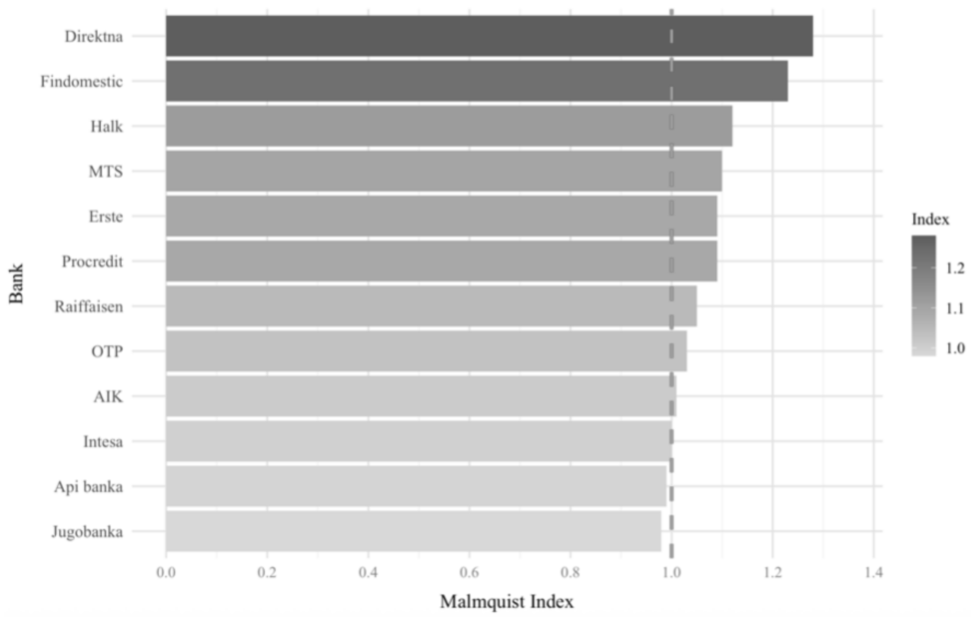

Figure 4. Malmquist index, selected banks, 2010-2024

Source: Authors' calculations using the R programming language

The Malmquist index analysis was used to assess changes in the total productivity of banks throughout the observed period. The results revealed a general trend of improving productivity in the observed banking sector. The average Malmquist index for the majority of banks, representing more than 85% of the sample, was above unity, which clearly indicates a major improvement in productivity during the analyzed period. Decomposing the Malmquist index reveals that the overall productivity growth (MPI > 1 for over 85% of banks) was driven primarily by technological change (average of 1.036), while productivity change remained stable (average of 0.998). This indicates that Serbian banks benefited from technological improvements – such as digitalization and process optimization – rather than from catching up to the efficiency frontier. Direktna Bank and Findomestic Bank, with an index of 1.227, stood out in particular, as they recorded the most significant productivity growth. At the same time, the Bank of China and Intesa achieved stable performance with a Malmquist index of exactly 1.00 and a standard deviation of zero, confirming their status as efficient leaders.

Based on the value of the Malmquist index, banks can be grouped into several categories. After Direktna and Findomestic, there are banks with a moderate improvement (Malmquist between 1.05 and 1.15), such as Halkbank, MTS, Erste and ProCredit Bank. Most of the banks in the sample belong to the stable performance category, with an index in the range of 0.95–1.05. A slight deterioration in productivity was recorded at Api bank (0.986) and Jugobank (0.979).

The final phase of the research involved consolidating all metrics into a panel dataset, enabling a comprehensive evaluation of banks' performance through multidimensional analysis. In addition to the combined analysis of technical efficiency, super-efficiency and the Malmquist index, panel data were used to include additional performance analyses, namely temporal consistency and ability to recover. This comprehensive approach made it possible to identify the top ten banks using an overall score that takes into account the values of all previously mentioned applied techniques.

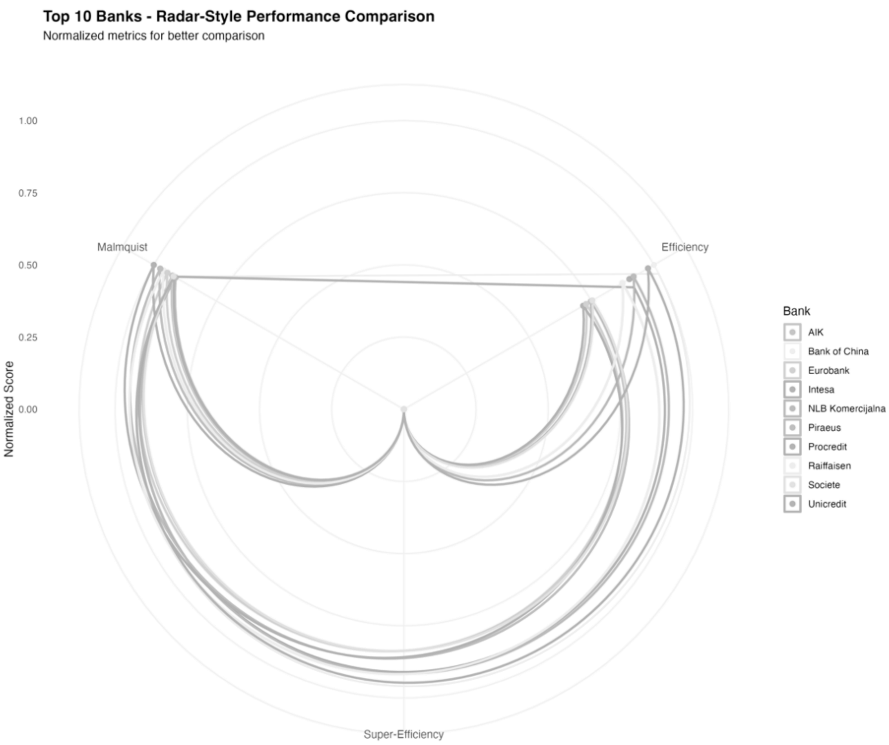

Figure 5. Top 10 banks, 2010-2024

Source: Authors' calculations using the R programming language

The analysis of the leading banks, according to the overall score, indicates that success in the banking market requires continuous maintenance of high efficiency over time. When we focus on banks with the longest available time series that are still present on the market, Banca Intesa and UniCredit Bank stand out as the absolute leaders. These two banks not only record extremely high average efficiency values (0.808 and 0.875, respectively) but also consistently rank at the very top and belong to the category of banks that demonstrate long-term improvement. Their ability to maintain high positions over the observed period indicates resistance to macroeconomic fluctuations and well-established resource management models.

After the above-mentioned banks comes Raiffeisen Bank, which achieves a very high total score (63.7) and an efficiency of 0.783. Raiffeisen Bank is also classified in the "improving" category, indicating that systemically important banks in the domestic market are able to find adequate models for long-term productivity growth. Its stable progress over time, along with the recorded improvement of the Malmquist index, shows that technological innovation and cost optimization play a significant role in maintaining competitiveness in the banking market of the Republic of Serbia.

Banks such as ProCredit Bank, AIK Bank and Eurobank are in the middle segment of average efficiency, but they are all dominantly classified as banks in the recovering phase. Although their average efficiency indices are slightly lower, ranging from 0.643 to 0.670, their long-term survival and overall scores indicate a strong capacity. From the above, it can be concluded that long-term continuity in the banking sector does not depend solely on consistently high operational efficiency, but on an institution's ability to absorb shocks, overcome periods of inefficiency, and improve performance in the long term.

The sustained high efficiency of Banca Intesa and UniCredit over the entire 15-year period reflects not only operational excellence but also structural advantages, including diversified corporate and retail portfolios, access to international liquidity, and continuous investment in digital platforms. In contrast, the volatility of Jugobank's efficiency scores is likely driven by frequent ownership changes and governance instability, which have disrupted long-term strategic planning. The recovery of banks such as ProCredit and AIK is linked to post-crisis restructuring, cost rationalization, and gradual digitalization.

The next section presents the results and discussion of the efficiency of the banking sector in Montenegro.

Table 2 presents the list of inputs and outputs. These variables were selected based on the literature review presented in the previous section. The first step in the analysis was to create a correlation matrix to identify potential multicollinearity problems between the input variables. High correlation coefficients (over 0.8) between key financial indicators such as assets, capital, loans and total deposits indicated significant collinearity, which would lead to unstable DEA results if these variables were used simultaneously in the model. These results limited the model specification to a combination of two inputs instead of three; this eliminated the problem of multicollinearity and is expected to provide more robust efficiency estimates. The sample size of 15 DMUs exceeds the recommended threshold of 3×(inputs+outputs) = 9, ensuring robust and reliable DEA results with stable discriminatory power.

For the DEA models specification, input configurations with low correlation coefficients were selected to ensure optimal discrimination power. Specifically, the following combinations with low correlations were used: *Asset* and *Interest expenses* (0.156), *Capital* and *Interest expenses* (-0.009), *Labor costs* and *Interest expenses* (0.323), *Total deposits* and *Interest expenses* (0.112), and *Interest expenses* and *Number of employees* (0.449). This approach allowed *Interest expenses*, as the variable with the lowest correlation with the other inputs, to be used as a common element in all models, thereby avoiding the problem of multicollinearity. Since five different models were defined, we added three outputs to each of them, resulting in a total of 15 models to be tested.

Table 2. The list of inputs and outputs

Inputs	**Outputs**
Asset	*Total loans*
Capital	
Total Deposits	*Net profit or loss*
Interest expenses	
Labor costs	*Interest revenue*
Number of employees	

Source: Authors

Regarding the methodology, it is important to point out certain limitations of the research that primarily arise from objective characteristics of the market itself. The main limitation is related to the relatively small sample of 15 banks (DMU units). Although such a sample can reduce the discriminatory power of the model in standard DEA analysis, it nevertheless represents a realistic picture, as it includes the total number of banks in the banking sector of Montenegro. In order to compensate for the shortcoming, the survey was designed to cover a wider time horizon (from 2010 to 2024), thereby improving the reliability of trend analysis despite the limited cross-sectional dimension of the sample. In some specifications, such as Model 12, as many as 12 out of 15 banks were classified as fully efficient, indicating insufficient variation among DMUs. However, this limitation was mitigated by a) using an unbalanced panel spanning 15 years, which increases the number of observations for productivity analysis; b) testing 15 alternative specifications; and c) selecting models (e.g., Model 13) where only 6 banks were efficient, indicating reasonable discrimination. Nevertheless, the efficiency scores for Montenegro should be interpreted with caution, particularly given the high proportion of efficient banks.

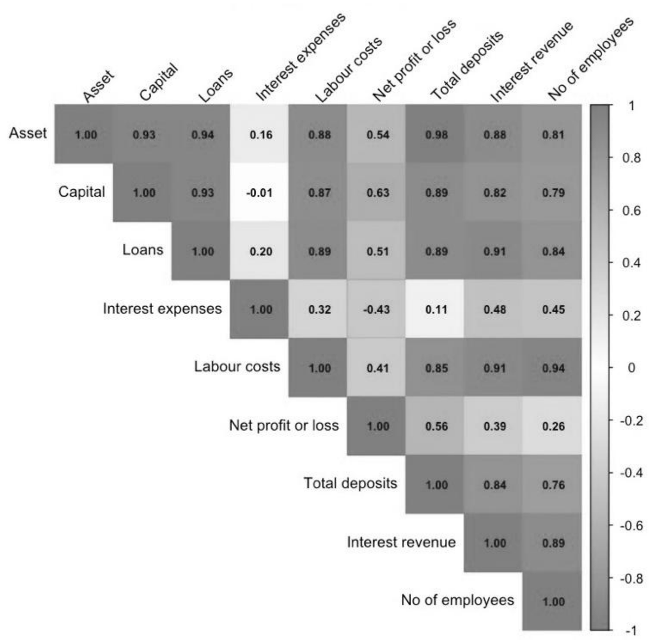

Figure 6. The correlation matrix

Source: Authors' calculations using the R programming language

Another limitation relates to the model specification and the panel structure itself. Due to the need to avoid the problem of multicollinearity in a small sample, the selected model focuses on the most important inputs and outputs (capital and interest), deliberately omitting certain operating costs and non-interest income. In addition, due to the turbulent 14-year period, the sample includes banks that subsequently went bankrupt (such as Atlas and Invest Bank), resulting in unbalanced panel data. Although the applied Malmquist index is methodologically completely adequate and capable of measuring changes in productivity even in such unbalanced panels, fluctuations in the number of active market participants over time remain a specific limitation that should be taken into account when interpreting the long-term stability of the entire sector.

Figure 7 presents a comparative analysis of the efficiency distribution obtained using different BCC DEA models, with the type of output variable highlighted in color. BCC efficiency values are grouped according to values ranging from 0 to 1. Three main output variables – *interest revenue*, *loans* and *net profit or loss* – are used to compare model performance. The graph provides insight into which models achieve higher efficiency in relation to different outputs, as well as whether efficiency is consistent across output variables. Notably, models that use *interest revenue* as an output produce higher efficiency scores compared to the other two groups of models.

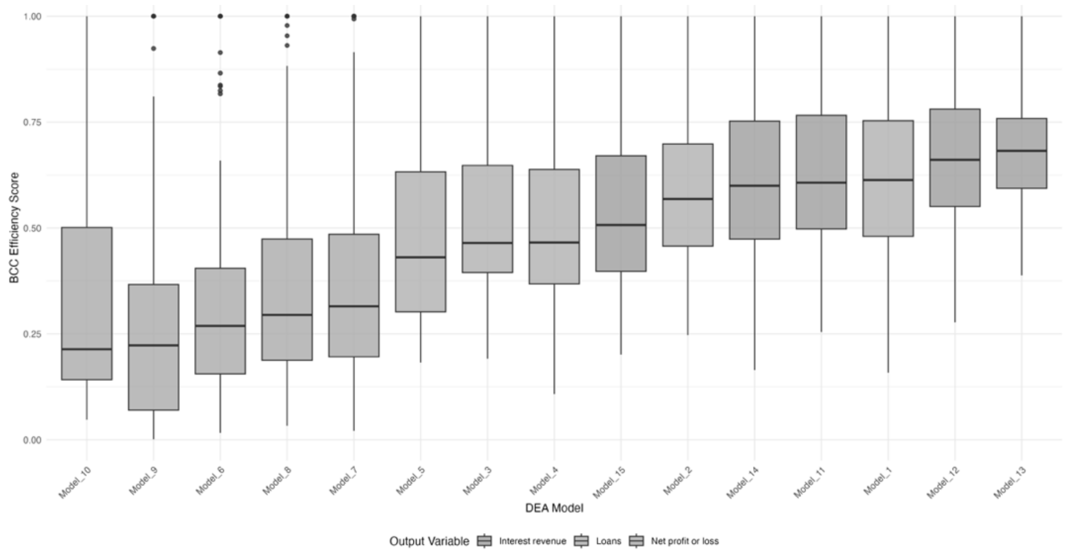

Figure 7. Comparative efficiency distribution across DEA Models

Source: Authors' calculations using the R programming language

After the BCC DEA analysis was conducted for all 15 models, a comprehensive evaluation was conducted to identify the most robust and reliable models. The evaluation was based on six key criteria: average efficiency, the number of fully efficient DMU units, stability of results as measured by the coefficient of variation, resistance to outliers, discriminatory power, and consistency within the distribution.

Table 3. Overall model scores

Model	Mean	No. of efficient DMU	CV	Outliers	SD	Discrimination	Consistency
Model_13	0.6860	6	19.03	0	0.1306	0.892	0.242
Model_12	0.6678	12	25.62	3	0.1711	1.083	0.348
Model_11	0.6217	9	30.48	8	0.1895	1.200	0.442
Model_1	0.6137	6	32.33	9	0.1984	1.371	0.446
Model_14	0.6096	10	33.93	13	0.2068	1.370	0.465
Model_2	0.5891	9	30.35	6	0.1788	1.278	0.425

Model	Mean	No. of efficient DMU	CV	Outliers	SD	Discrimination	Consistency
Model_15	0.5518	9	38.27	18	0.2112	1.448	0.538
Model_3	0.5316	5	36.64	8	0.1948	1.521	0.544
Model_4	0.5101	9	42.69	35	0.2178	1.749	0.580
Model_5	0.4903	6	46.44	44	0.2277	1.668	0.767
Model_7	0.3681	8	65.19	84	0.2400	2.660	0.919
Model_8	0.3656	7	66.52	94	0.2432	2.644	0.971
Model_10	0.3428	6	78.63	113	0.2695	2.779	1.681
Model_6	0.3100	7	74.07	103	0.2296	3.173	0.927
Model_9	0.2664	6	90.45	117	0.2409	3.749	1.331

Source: Authors' calculations using the R programming language

Based on a comprehensive performance analysis of 15 different BCC DEA models, Models 13, 12, and 11 clearly stand out as the most reliable and efficient choices for evaluation. This conclusion comes from their superiority in key features that measure not only average efficiency, but also the reliability of the results themselves. Firstly, these models achieve the highest average efficiency scores (0.686, 0.668 and 0.622), which directly indicates that the observed banks (DMUs) achieve the best relative efficiency according to these models. Secondly, these models demonstrate remarkable consistency and reliability. This is supported by their lowest coefficients of variation (CV) – 19.03%, 25.62% and 30.48%. These lowest coefficients of variation mean that the efficiency results are grouped around the average, without large oscillations, which indicates the homogeneity of the results, that is, the consistency of the results.

Finally, these models have the lowest number of outliers (0, 3 and 8). The small presence of extreme values confirms that the models accurately represent the majority of units in the dataset, without unbalanced results that can distort the overall picture. In contrast, models with a lower average (such as Model 9 or Model 4) show a very high CV and a large number of outliers, which makes them inconsistent and unreliable for drawing conclusions. Therefore, the combination of high average efficiency, statistical consistency (low CV) and minimal influence of outliers makes Models 13, 12 and 11 the optimal choice for reliable efficiency analysis.

Based on the analysis presented thus far, we tested all three different DEA approaches proposed by Paradi, Rouatt & Zhu, 2011; Tuškan & Stojanović, 2016; Maradin, Olgić & Benković, 2018: the production approach, the intermediary role and the profitability approach. Following a comprehensive evaluation that revealed the most robust and reliable models, we focused on the profitability approach. Although Model 13 demonstrated slightly superior statistical properties, Model 12 was selected as the primary specification for three substantive reasons: (1) capital represents a strategic resource with long-term implications for banking stability and competitiveness; (2) the transparency of the relationship between capital structure, funding costs, and interest revenue facilitates practical interpretation for decision-makers; (3) in the context of Montenegro's euroized economy with limited monetary policy tools, capital adequacy emerges as a critical determinant of banking sector resilience (Žugić & Fabris, 2014).

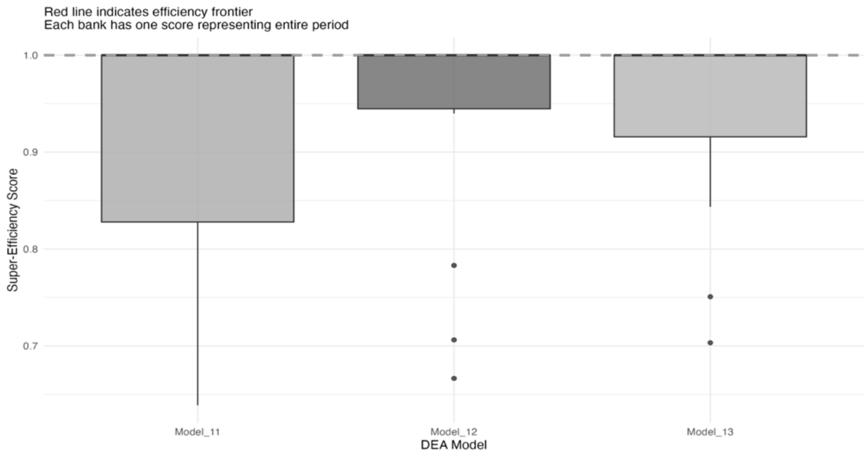

Figure 8. Comparative Super-Efficiency Scores

Source: Authors' calculations using the R programming language

Another type of DEA sensitivity analysis is based on the super-efficiency DEA approach in which a test DMU is not included in the reference set (Zhu, 2001). In a classical DEA method (either BCC or CCR), a DMU is compared to a "best DMU" that includes that DMU itself. This creates the problem of the efficiency limit, and it is not possible to rank which of them is the most efficient; instead, clusters are formed at the limit. The super-efficiency model solves this problem because, when evaluating the efficiency of a DMU, it is excluded from the data set with which it is compared.

The results shown in Figure 8, Comparative Super-Efficiency Scores, present the comparative efficiency of the three DEA models during the entire observed period - the models with the highest average BCC efficiency and the lowest variability. It is noticeable from the graph that Model 13 achieves the highest super-efficiency scores, confirming its status as not only the most efficient but also the most rigorous model, whose efficiency limit imposes the highest standards. Model 12 occupies an intermediate position, showing moderate rigor, while Model 11, although solid, represents the least demanding approach. The dominant position of Model 13, characterized by high and consistent scores, indicates its robustness and makes it the optimal choice for reliable unit ranking and strategic decision-making, while Model 12 can be considered a useful compromise. Here it is important to note once again that all three models, in addition to interest expenses as input and Interest revenue as output, include: Model 11 - assets, Model 12 - capital, and Model 13 - labor costs. Based on these three models, banks with super-efficiency scores are Ziraat Bank Montenegro, Erste Bank Podgorica, Crnogorska Komercijalna Bank and Adriatic Bank Podgorica.

Although all three models (11, 12 and 13) stood out in terms of performance during the evaluation, the final decision to use Model 12 as the primary specification for further analysis was based on its strategic importance of capital as a key resource in banking operations and its central role. Additionally, there is a negative correlation between capital and interest expenses (-0.009), which supports the claim that banks with larger capital borrow on more favorable terms. Bearing in mind the characteristics of Montenegro's banking sector, assets and employee costs are less appropriate than capital for assessing efficiency. The specification of this model enables the analysis of how banks optimize their capital structure and manage funding costs to generate income, which forms the basis of banking operations. This transparency in the relationship between input-output variables not only increases the validity of the results but also facilitates decision makers to formulate specific recommendations for improving efficiency, making Model 12 not only statistically robust but also a practically applicable tool for improving bank performance. However, Model 12 (Capital + Interest expenses → Interest revenue) achieved the largest number of fully efficient DMU units (12 banks), which requires further analysis.

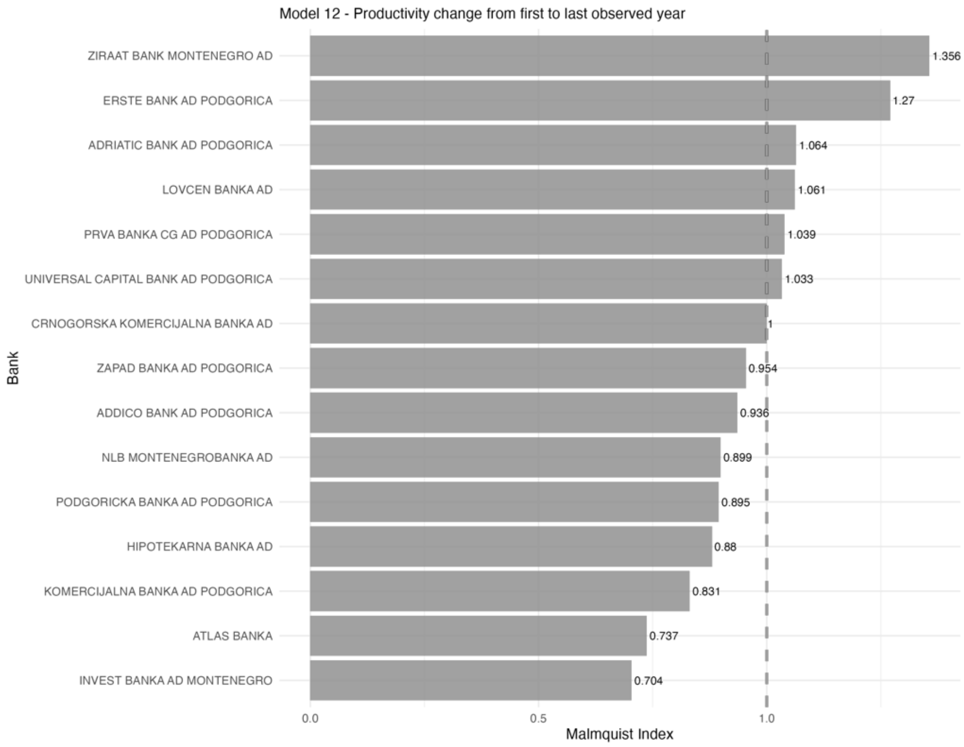

Figure 9. The Malmquist index, 2010-2024

Source: Authors' calculations using the R programming language

When evaluating how bank productivity evolves, the Malmquist index approach typically breaks down the results into two components. One is the 'catching-up' effect (representing productivity changes of individual banks), and the other is the frontier shift, which is generally driven by technological progress. Calculating Malmquist indices from DEA window analysis scores raises the problem of how to define the same period frontier in a window analysis (Asmild et al., 2004). The analysis of the Malmquist index for Model 12 reveals significant variations in the productivity of the Montenegro banking sector during the observed period. Although all banks maintained full technical efficiency (productivity change = 1), which indicates the stability of their relative position within the sector, overall productivity shows marked differences. The observed productivity coincides with two significant periods of economic challenge in Montenegro: the European debt crisis (2011-2013) and the COVID-19 pandemic (2020-2021). This temporal alignment suggests that external macroeconomic shocks disproportionately affected certain banks' ability to maintain productivity, despite their preserved technical efficiency. We note that this temporal alignment is descriptive and does not imply causality. Formal testing would require a two-stage DEA or panel regression analysis, which is beyond the scope of this paper. The superior performance of Ziraat Bank Montenegro (1.356) and Erste Bank (1.270) may be attributed to their access to international parent company technologies and risk management systems, highlighting the potential competitive advantage of foreign-owned banks in navigating economic turbulence. The biggest decline was recorded by Atlas Bank (0.737) and Invest Bank (0.704). These results suggest that some banks have adapted more successfully to changing market conditions and taken advantage of technological advances, while others have experienced a decrease in their competitive ability. A productivity change of 1 for all banks does not imply that no bank improved its operations. Rather, it is an artifact of the small sample, the unbalanced panel, and the BCC model, which tends to classify many banks as efficient each period. Thus, the technological change component drives the overall MPI, while the productivity change component is flattened by the limitations of the sample.

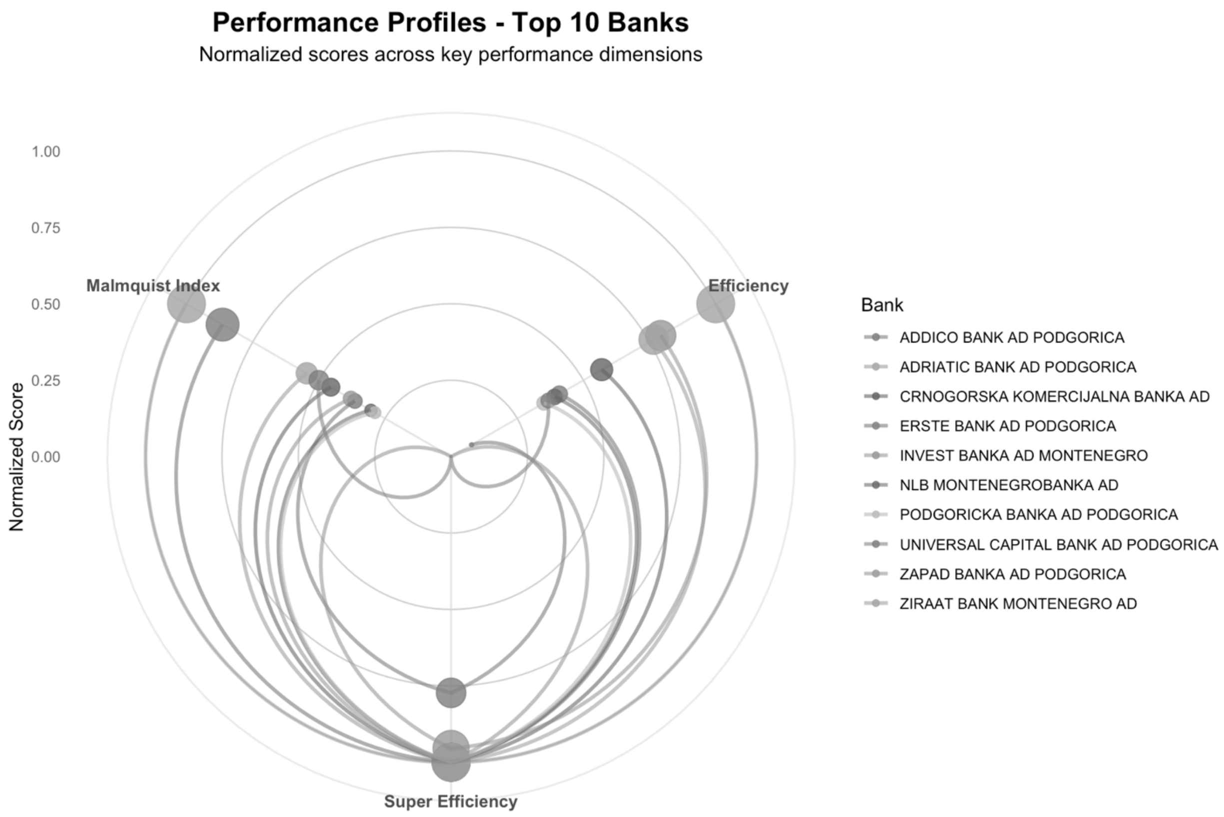

Figure 10. Comparative analysis of Efficiency, Super-efficiency and Malmquist index

Source: Authors' calculations using the R programming language

Figure 10 shows a comparative analysis of DEA results - efficiency, super-efficiency and Malmquist index. The comparative analysis reveals significant differences in the efficiency of operations of the first ten banks in Montenegro. This triple dimension indicates the heterogeneity in management capabilities and operational efficiency of banks operating in the market. Adriatic Bank AD Podgorica dominates according to the technical efficiency indicator (0.648), while Ziraat Bank Montenegro AD achieves the highest Malmquist index (1.36), suggesting an exceptional ability of this bank to improve productivity over time and adapt to market conditions. It is notable that most banks achieve maximum super-efficiency (1.00), which indicates the robustness of their business model. These findings suggest that successful banks do not rely solely on static efficiency, but combine operational excellence with continuous productivity improvement, thereby achieving a sustainable competitive advantage in the market. Additionally, this distribution indicates substantial structural differences in banks' ability to respond to changing market conditions, implement digital transformations, and respond to changes in the regulatory framework.

The apparent contradiction between high technical efficiency (BCC scores near 1) and negative productivity growth (Malmquist<0.75 for several banks) is explained by external constraints: the euroized economy limits monetary accommodation, while the tourism-dominated GDP makes bank revenues highly seasonal and vulnerable to external shocks (e.g., COVID-19, the European debt crisis). Banks cannot adjust funding costs or interest margins independently, so even well-managed banks experience productivity declines when the real economy contracts. The superior performance of foreign-owned banks (Ziraat, Erste) is attributed to knowledge transfer and advanced risk management from their parent banks, which helped them navigate economic turbulence more effectively.

CONCLUSION

This research provides a comprehensive analysis of the operational efficiency and productivity dynamics of the banking sectors of Serbia and Montenegro during the period 2010 to 2024. Using unbalanced panel data and advanced non-parametric techniques (BCC DEA, super-efficiency and Malmquist index), the research offers deeper insight into resource management mechanisms under different macroeconomic conditions.

The findings of this study provide comprehensive insights into the research questions established at the beginning. The empirical results reveal a divergence in productivity trends between the two analyzed sectors. While the Serbian banking market demonstrates stable and continuous productivity growth, the Montenegrin sector exhibits high technical efficiency scores that, however, mask a concerning regression in overall productivity. Furthermore, the research validates the necessity of a customized methodological framework. The results confirm that applying market-specific specifications - the profitability approach for Montenegro and the intermediary approach for Serbia- was essential for ensuring the robustness of the analysis and for accurately capturing the unique operational characteristics of each emerging market.

The main contribution of the work lies in the application of a double methodological approach that respects the structural differences of the analyzed markets. The application of the profitability approach for Montenegro proved crucial for understanding the banking system operating under conditions of euroization. The results for the Montenegrin market reveal a specific paradox: although banks exhibit high internal technical efficiency, the Malmquist index analysis indicates a structural regression of productivity over time. This suggests that external constraints, the high concentration of the economy, and the limited size of the market outweighed the banks' internal optimization efforts.

In contrast, the application of the intermediary approach to the banking sector in Serbia confirms that traditional financial mediation still represents a stable foundation for growth in conditions of active monetary policy. The Serbian market shows overall progress, with more than 85% of observed banks achieving productivity growth. Leading systemic banks (such as Banca Intesa and UniCredit Bank) have demonstrated exceptional resilience and ability to maintain the highest levels of efficiency throughout the observed period. Additionally, the analysis of banks in the recovery phase indicates that long-term capacity to absorb shocks and undergo restructuring is as important as short-term operational efficiency.

Comparing our results with previous empirical studies reveals both similarities and differences. For Serbia, the dominance of technological change in driving productivity growth aligns with Laporšek, Trunk & Stubelj (2022) for European banks. For Montenegro, the paradox of high technical efficiency but low productivity growth contrasts with Milenković et al. (2022), who reported positive size-efficiency relationships in the Western Balkans; this divergence may be explained by Montenegro’s euroization and high economic concentration, which constrain traditional intermediation. Our tailored methodological approach - using different DEA specifications for the two countries – extends the literature by showing that uniform models can produce misleading results when markets differ fundamentally.

Based on the empirical findings, several tentative implications emerge. First, given that productivity growth in Serbia was driven primarily by technological change, banks may benefit from continued investment in digitalization and process innovation. Second, in Montenegro, where high technical efficiency masks declining productivity, regulators could consider policies that encourage knowledge transfer from foreign-owned banks to domestic ones. Third, persistent productivity decline despite technical efficiency suggests that market consolidation may be inevitable. However, these implications are indicative, not causal, and require further validation.

Several limitations should be acknowledged: the small sample size in Montenegro, the unbalanced panel, the lack of formal outlier and monotonicity tests, the descriptive discussion of external shocks, and the atypical business model of the Bank of China. These limitations do not invalidate the main conclusions but should be considered when interpreting the results.

In conclusion, this research confirms that an objective picture of the efficiency of the banking sector cannot be obtained by applying universal models; instead, a market-driven and customized approach that respects the specifics of each individual market is necessary when selecting inputs and outputs. To ensure the robustness of the results, the methodological framework must go beyond standard DEA analysis and integrate super-efficiency and the Malmquist index to track dynamic changes in productivity over time. Through a comprehensive approach, it is possible to identify the real sources of competitiveness and long-term viability of banks.

Regarding future research, the analysis could be broadened in several directions. First, expanding the sample to include other Western Balkan countries would allow for a more comprehensive regional benchmarking of banking efficiency. Second, incorporating macroeconomic indicators, such as GDP growth rates and inflation as environmental variables in a two-stage DEA model could provide deeper insights into how external factors influence productivity. Finally, future studies might explore the inclusion of qualitative factors, such as digitalization levels or ESG scores, to reflect the challenges of the banking industry.

REFERENCES

Aigner, D., Lovell, C., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics,* 6(1), 21-37. https://EconPapers.repec.org/RePEc:eee:econom:v:6:y:1977:i:1:p:21-37.

Andersen, P., & Petersen, N. C. (1993). A Procedure for Ranking Efficient Units in Data Envelopment Analysis. *Management Science*, 39(10), 1261–1264. DOI: 10.1287/mnsc.39.10.1261

Asmild, M., Paradi, J. C., Aggarwall, V., & Schaffnit, C. (2004). Combining DEA window analysis with the Malmquist index approach in a study of the Canadian banking industry. *Journal of productivity analysis*, *21*(1), 67-89.

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), 1078-1092.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research*, *2*(6), 429-444.

Dyson, R. G., Allen, R., Camanho, A. S., Podinovski, V. V., Sarrico, C. S., & Shale, E. A. (2001). Pitfalls and protocols in DEA. *European Journal of operational research*, 132(2), 245-259.

Enguene, A.A. (2025). Does Bank Capital Increase the Productivity of the Banking Industry? A Critical Review. *Journal of Central Banking Theory and Practice*, 14(3), 5-34.

Färe, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries. *American Economic Review*, 84(1), 66–83.

Hair Jr, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis. In *Multivariate data analysis* ,785-785.

Kaličanin, T., & Terzić, I. (2023). Measures of concentration level in the banking sector: Empirical evidence from Serbia, Croatia and Montenegro. *The European Journal of Applied Economics*, *20*(1), 107-121.

Krmac, E., & Mansouri Kaleibar, M. (2023). A comprehensive review of data envelopment analysis (DEA) methodology in port efficiency evaluation. *Maritime Economics & Logistics*, *25*(4), 817-881.

Laporšek, S., Trunk, A., & Stubelj, I. (2022). Productivity Change in European Banks in the Post-Crisis Period. *Systems* 2022, 10, 186.https://doi.org/10.3390/systems10050186

Maradin, D., Drazenovic, B. O., & Benkovic, S. (2018). Performance evaluation of banking sector by using DEA method. In H. Ribeiro, D. Naletina, & A. L. da Silva, A. (Eds.). Proceedings of the 35th International Scientific Conference on Economic and Social Development – Sustainability from an Economic and Social Perspective (pp. 684-690).Varazdin Development and

Entrepreneurship Agency. https://www.researchgate.net/publication/330183582_Performance_evaluation_of_banking_sector_by_using_DEA_method
Milenkovic, N., Radovanov, B., Kalaš, B., & Horvat, A.M. (2022). External Two Stage DEA Analysis of Bank Efficiency in West Balkan Countries. *Sustainability* 2022, 14, 978. https://doi.org/10.3390/su14020978
Mirković, V., Matić, M. I., & Dudić, B. (2024). Measuring Of Banking System Resilience By Using The Texas Ratio. *The European Journal of Applied Economics*, *21*(1), 48-59.
Nataraja, N. R., & Johnson, A. L. (2011). Guidelines for using variable selection techniques in data envelopment analysis. *European Journal of Operational Research,* 215(3), 662-669.
Othman, F.M., Mohd-Zamil, N.A., Rasid, S.Z.A., Vakilbashi, A., & Mokhber, M. (2016). Data Envelopment Analysis: A Tool of Measuring Efficiency in Banking Sector. *International Journal of Economics and Financial Issues*, 6(3), 911-916.
Paradi, J. C., Sherman, H. D., & Tam, F. K. (2018). Data Envelopment Analysis in the Financial Service Industry. A Guide for Practitioners and Analysts Working in Operations Research Using DEA (1st ed.). Springer. https://doi.org/10.1007/978-3-319-69725-3
Paradi, J. C., Rouatt, S., & Zhu, H. (2011). Two-stage evaluation of bank branch efficiency using data envelopment analysis. *Omega*, *39*(1), 99-109.
Radojević, T., Kesić, M., Rajin, D., & Butėnas, R. (2023). Presentation of disclosures related to credit risk of a certain bank. *The European Journal of Applied Economics*, *20*(1), 66-92.
Tekić, D., Mutavdžić, B., Milić, D., Zekić, V., & Novaković, T. (2021). Primena DEA metode u oceni efikasnosti poslovanja banaka u Republici Srbiji, *Letopis Naučnih Radova / Annals Of Agronomy*, 44 (2), 149-157.
Tuškan, B., & Stojanović, A. (2016). Measurement of cost efficiency in the European banking industry. *Croatian Operational Research Review*, 7(1), 47-66.
Zhu, J. (2001). Super-efficiency and DEA sensitivity analysis. *European Journal of operational research*, *129*(2), 443-455.
Central Bank of Montenegro. (2025). https://www.cbcg.me/en/publications/regular-publications/central-bank-of-montenegro-annual-report

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APPENDIX

Table 1a. Efficiency trend based on Malmquist index, Serbian banking sector, 2010-2024, selected banks

Bank	Trend
DIREKTNA BANK AD	Strong Progress
HALK BANK AD	Strong Progress
PROCREDIT BANK AD	Progress
ERSTE BANK AD	Progress
RAIFFAISEN BANK AD	Progress
OTP BANK AD	Progress
EUROBANK BANK AD	Progress
ADIKO BANK AD	Progress
AIK BANK AD	Progress
SOCIETE BANK AD	Stable
INTESA BANK AD	Stable
UNICREDIT BANK AD	Stable
API_BANK BANK AD BANK AD	Strong regress
JUGOBANK	Strong regress

Source: Authors' based on R programming language result

Table 2a. Efficiency trend based on Malmquist index, Montenegrin banking sector, 2010-2024

Bank	Trend
ZIRAAT BANK MONTENEGRO AD	Strong Progress
ERSTE BANK AD PODGORICA	Strong Progress
LOVCEN BANK AD	Progress
PRVA BANK CG AD PODGORICA	Progress
ADRIATIC BANK AD PODGORICA	Progress
UNIVERSAL CAPITAL BANK AD PODGORICA	Progress
CRNOGORSKA KOMERCIJALNA BANK AD	Stable
ZAPAD BANK AD PODGORICA	Regress
ADDICO BANK AD PODGORICA	Regress
NLB MONTENEGROBANK AD	Strong Regress
PODGORICKA BANK AD PODGORICA	Strong Regress
INVEST BANK AD MONTENEGRO	Strong Regress
HIPOTEKARNA BANK AD	Strong Regress
ATLAS BANK	Strong Regress
KOMERCIJALNA BANK AD PODGORICA	Strong Regress

Source: Authors' based on R programming language result