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Assessing and forecasting the efficiency of Russian banks (2000–2026): A DEA, panel data, and Monte Carlo simulation approach

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Abstract

This study aims to evaluate the efficiency of Russian banks, identify the factors influencing it based on their size and ownership type, and forecast future trends in the banking sector. The analysis utilized data from 680 Russian banks over the period 2000–2023, employing Data Envelopment Analysis (DEA) to measure technical efficiency, panel data analysis to determine efficiency-related variables, and Monte Carlo simulation to predict future performance for the years 2024–2026. The findings indicate a general decline in bank efficiency over time, driven by economic and political crises, particularly those linked to oil price fluctuations and sanctions. The study reveals that an increase in client funds (non-credit organizations) and higher leverage ratios are associated with improved bank efficiency. Among bank categories, mega-banks with assets exceeding 1.05 trillion rubles demonstrated the highest efficiency, followed by medium banks, large banks, and small banks, respectively. Moreover, Russian domestic banks exhibited higher efficiency levels compared to their foreign counterparts. The study forecasts continued increases in interest rates in the coming years, driven by the instability of the local currency and rising inflation caused by the Russia–Ukraine conflict. Significant changes in client funds (non-credit organizations) are also anticipated, with a decline expected in 2024, a temporary increase in 2025, and another decline in 2026. These fluctuations reflect instability stemming from corporate performance downturns and capital outflows due to economic sanctions. In addition, the operational efficiency of Russian banks is expected to decline, with an increase in the proportion of distressed banks, especially among small and large banks struggling with rising funding costs. The study concludes that funding sources, associated costs and leverage are the most important factors affecting the efficiency of Russian banks.

Keywords: Russian banks, data envelopment analysis, DEA, panel data analysis, Monte Carlo simulation, financial performance, bank forecasting.
JEL classification: G21, G32, G39.

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1. Introduction

Bank efficiency is a pivotal topic in economic studies due to its significant influence on financial system stability and economic growth. In the context of the Russian economy, banks serve as fundamental drivers of economic development. However, the performance of the Russian banking sector has experienced considerable fluctuations, driven by factors such as economic crises, political instability, and international sanctions. Analyzing the efficiency of Russian banks, therefore, necessitates a comprehensive study that considers various dimensions influencing their performance, including time, geographic location, size, and ownership type.

Previous studies have explored the efficiency of Russian banks from multiple perspectives, such as geographic location, size, and ownership type, offering valuable but incomplete insights. For instance, several studies have demonstrated the superior performance of Moscow-based banks compared to regional banks during specific periods, while others have highlighted the greater efficiency of smaller regional banks under certain conditions. Additionally, some research has revealed that foreign banks outperformed domestic ones in terms of efficiency, whereas other analyses have suggested that regulatory factors might hinder performance. Further studies have investigated the effects of financial leverage and risk on bank performance. Despite these diverse research efforts, most studies have been limited by their temporal scope, the dimensions they address, or the relatively small sample size of banks analyzed. Moreover, methodological differences between studies have made it difficult to compare their findings, thereby limiting the ability to derive comprehensive and reliable insights into banking efficiency. These limitations underscore the need for a study that applies a unified methodology across a large sample size and over an extended timeframe, enabling robust and in-depth analysis.

This study holds particular significance by addressing these research gaps. It spans more than two decades (2000–2023), covers a large sample of 680 Russian banks, and examines efficiency across multiple dimensions. The study evaluates the efficiency of Russian banks by integrating three comprehensive analytical approaches: Data Envelopment Analysis (DEA) to measure efficiency, panel data analysis to understand the factors affecting efficiency, and Monte Carlo simulations to forecast future bank performance. Through these methods, the study aims to provide holistic and actionable insights while identifying strategies to enhance bank efficiency under current economic conditions.

2. Literature review

Many studies have analyzed the efficiency of Russian banks using different methodologies and dimensions, leading to varied outcomes influenced by temporal contexts, methodologies, and analytical focuses.

Several studies have assessed the efficiency of Russian banks based on geographic location. Golovan et al. (2008) proposed a model incorporating factor prices and variables related to asset quality and risks, finding that Moscow banks were more efficient than regional banks during 2002–2005. A study by Golovan (2006) further confirmed that Moscow banks showed higher efficiency in loan issuance between 2003 and 2005.

Conversely, Petrov et al. (2021) highlighted the role of monopolistic central banks in cities like Moscow and St. Petersburg in shaping the regional banking system, noting efficiency disparities across regions. In contrast, Styrin (2005) found that Moscow banks were not always the most efficient, as some regional banks, with strong ties to local authorities, achieved higher efficiency. Similarly, Golovan et al. (2010) found that regional banks outperformed Moscow banks in efficiency from 2005 to 2006, a conclusion supported by Nazin (2010), who emphasized the superior performance of regional banks over Moscow banks.

Some studies analyzed Russian bank efficiency based on size. Nazin (2010) found that smaller banks were more efficient than larger ones, while Shilov and Zubarev (2021) revealed that larger banks exhibited higher financial resilience during the COVID-19 pandemic. Abu-Alrop (2021) demonstrated that medium banks outperformed both small and large banks in efficiency from 2008 to 2017. Meanwhile, Kumbhakar and Peresetsky (2012) argued that Russian banks generally operated below the optimal scale.

Other research explored Russian bank efficiency based on ownership type. Studies by Nazin (2010) and Golovan et al. (2010) found that foreign-owned banks outperformed domestic banks in efficiency. Sharma and Shebalkov (2013) used neural networks to analyze the performance of 883 Russian banks, focusing on key performance indicators like return on assets and debt-to-profit ratio. Additionally, Penikas (2015) highlighted how the complexity of Russia's regulatory environment negatively affected efficiency.

Despite the diversity of prior studies, they have notable limitations, including limited temporal coverage and small sample sizes. Additionally, most studies focus on specific dimensions (e.g., regions, size, or ownership), which restricts the generalizability of their findings.

This study aims to address these limitations by offering a comprehensive analysis from 2000 to 2023, covering 680 Russian banks. It utilizes three integrated approaches: DEA to assess efficiency, panel data analysis to identify influencing factors, and Monte Carlo simulation to forecast future performance (2024–2026). Additionally, banks are reclassified by asset size and ownership type, introducing new dimensions for analysis. This research seeks to fill existing gaps and provide novel, comprehensive insights into the efficiency of Russian banks, considering the significant economic transformations in Russia over the past two decades.

3. Data and methodology

This study adopts the perspective that balance sheet items, representing sources and uses of funds, are variables banks can manage and control, while traditional performance indicators reflect the outcomes of banks' management of their balance sheets. Accordingly, the study initially selects all balance sheet items divided by total assets as independent variables (inputs). In contrast, the dependent variables (outputs) are traditional performance ratios: return on assets (ROA), return on equity (ROE), and net interest margin (NIM). Statistical techniques, including regression analysis and DEA, are used to exclude insignificant variables, narrowing the initial 24 variables to a refined subset.

The primary objective of this study is to assess the efficiency of Russian banks, identify key determinants of their efficiency based on size and ownership structure, establish a robust efficiency measurement, and forecast future trends in the Russian banking sector.

The study employs the DEA model to evaluate the technical efficiency of the decision-making units (DMUs) under review due to its flexibility in handling multiple inputs and outputs without requiring predefined weights. DEA is an effective mathematical approach for measuring the relative efficiency of DMUs by defining the production frontier and assessing efficiency relative to this boundary (Charnes et al., 1978). The efficiency of a DMU is defined as the ratio of weighted outputs to weighted inputs, generalized by DEA using linear programming to maximize the efficiency of each DMU while ensuring no DMU exceeds an efficiency score of 1.

Based on foundational works by Dantzig (1951) and Farrell (1957), later enhanced by Charnes et al. (1978) and Banker et al. (1984), DEA has garnered significant attention from researchers such as Zhu and Cook (2008), Cooper et al. (2007), and Coelli et al. (2005). This study adopts the input-oriented model under the assumption of variable returns to scale (VRS), a suitable approach as it focuses on minimizing resource use while maintaining output levels. The VRS model is particularly relevant when firms are not operating at optimal levels due to factors like imperfect competition or regulatory constraints (Huguenin, 2012). Efficiency scores are calculated by comparing DMUs' relative performance against an optimal efficiency frontier based on specified inputs and outputs.

$$\text{Minimize } \theta_k. \tag{1}$$

Subject to

$$y_{rk} - \sum_{j=1}^{n} \lambda_j y_{rj} \leq 0, \;\; r = 1, ..., s, \tag{2}$$

$$\theta_k x_{ik} - \sum_{j=1}^{n} \lambda_j y_{ij} \geq 0, \;\; i = 1, ..., m, \tag{3}$$

$$\sum_{j=1}^{n} \lambda_j = 1, \tag{4}$$

$$\lambda_j \geq 0, \;\; \forall_j = 1, ..., n, \tag{5}$$

where: θ_k denotes the technical inefficiency of firm k; λ_j represents the weight associated with the outputs and inputs of firm j; y_{rk} denotes the quantity of output r generated by firm k; x_{ik} indicates the quantity of input i consumed by firm k; n denotes the number of firms to be evaluated; s stands for the number of outputs; m stands for the number of inputs.

After obtaining the efficiency scores of Russian banks through DEA, the study conducts a panel data analysis using the one-way effect within model to identify the factors influencing efficiency. This analysis explores the relationship between the dependent variable—efficiency scores derived from DEA—and the independent variables, which include financial ratios from the balance sheet as well as the interest rate.

The study adopts this approach because it integrates cross-sectional and time-series data, enabling the observation of individual differences among banks (e.g., management style, corporate culture) that remain constant over time but may influence efficiency. This method effectively controls for unobserved heterogeneity, which might otherwise bias the results. The model can be mathematically represented as follows:

$$EFF_{it} = \alpha_i + \beta X_{it} + \epsilon_{it}, \tag{6}$$

where: EFF_{it}—efficiency score of bank i at time t (dependent variable); α_i—bank-specific fixed effect capturing individual characteristics that do not change over time; X_{it}—a vector of independent variables (financial ratios and the interest rate); β—coefficient vector measuring the impact of independent variables on efficiency; ϵ_{it}—error term capturing unobserved factors and random disturbances.

This model provides a robust framework for identifying and quantifying the impact of key financial variables on bank efficiency while accounting for time-invariant heterogeneity across banks. The term α_i captures the time-invariant characteristics of each bank that could influence y_i. By using fixed effects, we eliminate bias from omitted variables that do not vary over time. The fixed effects model is estimated by transforming the data to remove α_i. This involves demeaning each variable:

$$\tilde{Y}_{it} = Y_{it} - \tilde{Y}_i, \; \tilde{X}_{it} = X_{it} - \tilde{X}_i, \; \tilde{\epsilon}_{it} = \epsilon_{it} - \tilde{\epsilon}_i, \tag{7}$$

where $\tilde{Y}_i$, $\tilde{X}_i$, and $\tilde{\epsilon}_i$ are the averages of Y_{it}, X_{it}, and ϵ_{it} over time t for bank i.

The transformed model becomes:

$$\tilde{Y}_{it} = \beta \tilde{X}_{it} + \tilde{\epsilon}_{it}. \tag{8}$$

This approach controls for unobserved, bank-specific effects. The fixed effects model was employed, which assumes no perfect multicollinearity, zero correlation between errors and independent variables, and time-invariant unobserved effects.

It is important to note that the fixed effects model does not inherently estimate an intercept a due to the within transformation applied to the data. However, for the sake of clarity and practical interpretation, the intercept a was estimated by applying the resulting equation to the actual dataset.

After estimating the regression equation, Monte Carlo simulation is employed to evaluate future scenarios for the efficiency of Russian banks. This methodology is chosen for its ability to address non-linear relationships, account for uncertainty in data, and provide probabilistic estimates that support informed decision-making.

The input variables $X = (x_1, x_2, ..., x_n)$ are represented by their respective probability distributions F_1, F_2, ..., F_n. Monte Carlo simulation generates M random samples $X^{(m)}$ for $m = 1, 2, \ldots, M$ and computes the corresponding outputs $Y^{(m)}$ using the following equation:

$$Y^{(m)} = f(X^{(m)}) + \epsilon^{(m)}. \tag{9}$$

The simulation results provide an empirical distribution of $Y^{(m)}$, which is used for further analysis. The $Y^{(m)}$ represents the simulation outputs, while $\epsilon^{(m)}$ reflects the randomness element. The resulting distribution from the simulation is analyzed to estimate the probabilities of various scenarios and provide quantitative insights into the future efficiency of banks.

The study sample consists of unbalanced panel data for 680 Russian banks during the period 2000–2023, representing the majority of Russian banks. The unbalanced nature of the data arises from changes in the number of banks over time due to the entry of new banks into the market, exits, or other reasons.

For data preprocessing suitable for DEA, zero and negative values were replaced with values close to zero. For outliers, a statistical method based on interquartile range (IQR) was applied to identify and adjust them to fit within acceptable boundaries. The total number of financially active units included in the analysis was 11,049. Financially distressed banks with extreme data, such as negative equity, accumulated losses, or the absence of core banking activities (lending and deposit-taking), were excluded. Such exclusions were justified as their data were often extreme, illogical, or close to zero, which could distort DEA results. Since DEA primarily focuses on evaluating efficient units, these excluded units were undoubtedly inefficient.

The excluded units, numbering 1,433, were nevertheless considered in the overall banking sector efficiency calculation through what the study terms the "adjusted efficiency average." Although these banks were not directly included in the DEA efficiency computation, they were considered part of the banking sector. A high proportion of distressed banks indicates an unstable or generally inefficient banking environment. Therefore, the adjusted efficiency average was calculated to reflect the actual situation more accurately using the following formula:

$$\begin{aligned}&\textit{Adjusted Efficiency Average} =\\ &= \textit{Efficiency Average of Active Banks} \times \left(1 - \frac{\textit{Number of distressed banks}}{\textit{Total number of banks}}\right). \qquad (10)\end{aligned}$$

Due to the potential loss of DEA's discriminatory power with a large number of variables (24 variables), the study employed statistical methodologies to reduce it. Key references for variable selection methodologies include Jenkins and Anderson (2003), Adler and Yazhemsky (2010), Luo et al. (2012), and Subramanyam (2016). Among these approaches, the most effective involved repeatedly running the DEA model while gradually excluding the least impactful variables. This process is a form of sensitivity analysis that strengthens the reliability and stability of the results. This iterative and robust method has been endorsed by numerous researchers as it allows input and output selection based on results without predefining them. Since the primary objective of DEA is to evaluate bank efficiency rather than determine variable effects, the study continued refining the variables until achieving the highest discriminatory power. Ultimately, the study selected Net loans outstanding / Total assets and Total deposits / Total assets as inputs, and Net interest margin as the output.

For the simulation, 10,000 simulations of different scenarios were conducted, assigning random values to independent variables within predefined bounds. These bounds were determined using an IQR-based statistical method to detect

Table 1
Variables and abbreviations used in the study.

Variable	Abbreviation	Proxy
Dependent variables (outputs)	ROE	Net profit or loss / Total equity
	ROA	Net profit or loss / Total assets
	NIM	Net interest margin / Net loans outstanding
Independent variables (inputs)	CAACTA	Cash and accounts in the Central bank / Total assets
	FICITA	Funds in credit institutions / Total assets
	NLOTA	Net loans outstanding/ Total assets
	FAIAINVTA	Fixed assets, intangible assets and inventories / Total assets
	LCBTA	Loans from the Central bank / Total assets
	FFCITA	Funds from credit institutions / Total assets
	CFNCOTA	Client funds (non-credit organizations) / Total assets
	DOITA	Deposits of individuals / Total assets
	DITA	Debt issued / Total assets
	IOCITA	Irrevocable obligations of a credit institution / Total assets
	GICITA	Guarantees issued by a credit institution / Total asset
	OOTA	Other obligations / Total assets
	SHFTA	Shareholder funds (capital) / Total assets
	ROFATA	Revaluation of fixed assets / Total assets
	TETA	Total equity / Total assets
	IRR	Interest rate ratio

Note: Total deposits include funds from credit institutions (FFCITA) client funds from non-credit organizations (CFNCOTA), and deposits of individuals (DOITA).
Source: Compiled by the author.

and adjust outliers, ensuring their alignment with realistic limits. Before running the simulations, several probability distributions (e.g., normal, log-normal, exponential) were tested for the independent variables using statistical goodness-of-fit tests, such as the Kolmogorov–Smirnov and Anderson–Darling tests. The distribution that best fits the historical data was selected based on the highest R-squared values, ensuring that the assumptions underlying the simulation were grounded in empirical data. To forecast changes in independent variables, the study employed a methodology that fitted various trend lines, including linear, polynomial, exponential, logarithmic, and power trends. The most representative trend line was selected based on data patterns and the coefficient of determination (R-squared).

The study classifies banks by efficiency degree into five groups, by asset size into four groups, and by ownership type into two groups. It is noteworthy that the data for this study were sourced from the Bank of Russia website.[1] Table 1 presents the variables used in this study.

4. Empirical results

4.1. Evaluating the efficiency of Russian banks using Data Envelopment Analysis (DEA)

After conducting DEA to assess the efficiency of the units, this study classified Russian banks into five groups based on their efficiency levels. Fig. 1 presents

[1] The data underpinning the analysis reported in this paper are deposited at Harvard Dataverse at https://doi.org/10.7910/DVN/DWUUQJ. The analysis was conducted using R 4.3.1 and Microsoft Excel 2019.

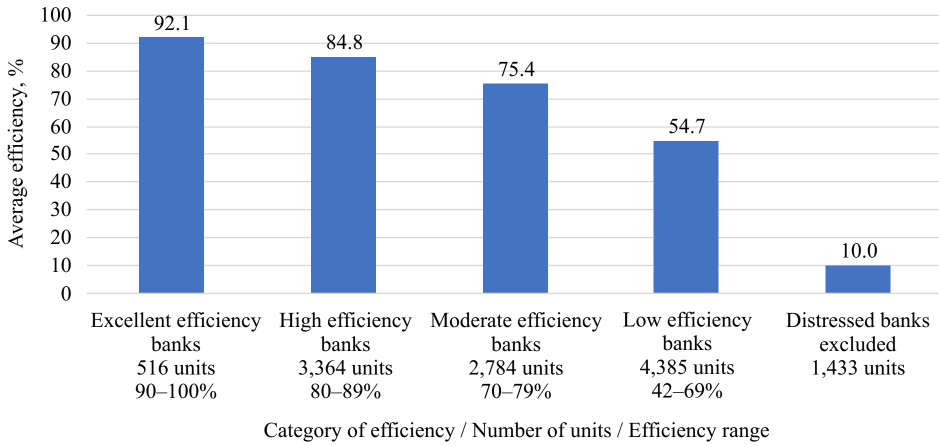

Fig. 1. Bank efficiency classification based on Data Envelopment Analysis (DEA).

Source: Author's calculations.

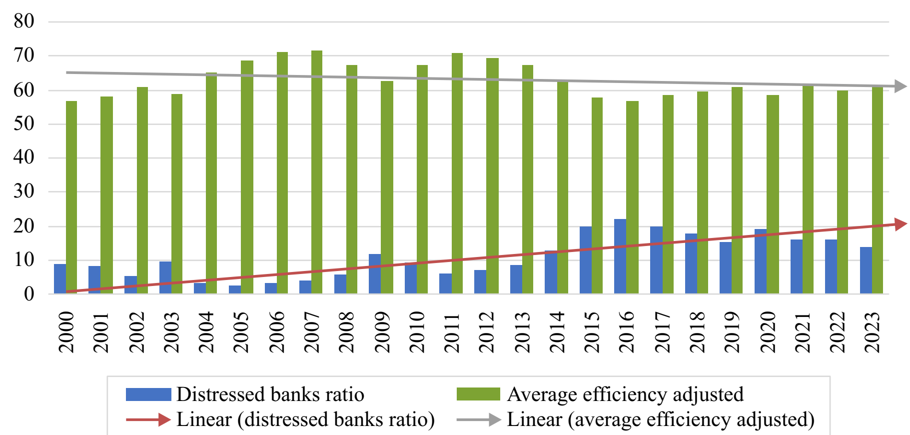

Fig. 2. Adjusted average efficiency and percentage of distressed banks in Russia (%).

Source: Author's calculations.

these groups, showing their efficiency ranges, the number of units in each group, and the average efficiency.

Fig. 2 illustrates the adjusted average efficiency of Russian banks and the percentage of distressed banks during the study period from 2000 to 2023. It is noticeable that Russian banks achieved the highest efficiency rates in 2007, 2006, and 2011, with efficiency reaching 71.6%, 71.2%, and 71%, respectively. This can be attributed to the significant surge in global oil prices, which bolstered the growth and stability of the Russian economy, heavily reliant on oil and gas revenues, thus fostering economic growth and relative stability.

In contrast, Russian banks experienced the lowest levels of efficiency in 2016, 2000, and 2015, with efficiency rates reaching 56.7%, 56.8%, and 57.6%, respectively. This reflects the financial crises faced by Russia, including the 1998 crisis, during which Russia defaulted on its debts, leading to a devaluation of the ruble and widespread banking crises. In 2015 and 2016, Russia endured a sharp decline in oil prices and sanctions imposed by the United States and the European Union, leading to economic stagnation and a further depreciation of the ruble. The impact of the COVID-19 pandemic in 2020 is also evident, as the pandemic severely affected the Russian economy, causing a drop in the efficiency of Russian banks to 58.4%.

Since the highest efficiency levels for Russian banks occurred in the first half of the study period, and the lowest levels occurred in the second half, excluding the year 2000, this suggests a downward trend in bank efficiency over time. The percentage of distressed banks reached its highest levels in 2016, 2017, and 2015, at 21.8%, 19.9%, and 19.7%, respectively. In contrast, the percentage of distressed banks was lowest in 2005, 2004, and 2006, at 2.3%, 3%, and 3.3%, respectively. These percentages align with the efficiency rates, indicating a rising trend in the percentage of distressed banks over time.

This review of the efficiency of Russian banks over the study period indicates that their efficiency has been significantly impacted by political and economic crises, with two main external factors influencing it: oil prices and sanctions.

4.2. Identifying variables affecting the efficiency of Russian banks using the fixed effects model (within model)

In this study, the fixed effects model (within model) is used to analyze the relationship and impact between bank efficiency and a set of independent variables as shown in the following equation:

$$\begin{aligned} Efficiency = {} & \beta_0 CAACTA + \beta_1 FICITA + \beta_2 CFNCOTA + \\ & + \beta_3 DOITA + \beta_4 DITA + \beta_5 TETA + \beta_6 IRR + \epsilon, \end{aligned} \tag{11}$$

where: β — coefficient vector measuring the impact of independent variables on efficiency; *CAACTA* — Cash and accounts in the Central bank / Total assets; *FFCITA* — Funds from credit institutions / Total assets; *CFNCOTA* — Client funds (non-credit organizations) / Total assets; *DOITA* — Deposits of individuals / Total assets; *DITA* — Debt issued / Total assets; *TETA* — Total equity / Total assets; *IRR* — Interest rate ratio; ϵ — error term.

After conducting a panel data analysis using the One-way Effect Within Model to identify the variables that influence efficiency, the results revealed a model with a Residual Sum of Squares (RSS) of 12.58 and a Total Sum of Squares (TSS) of 144.9. The R-squared value of 0.91 indicates that the model explains more than 91% of the variation in efficiency, while the adjusted R-squared of 0.90 further confirms the model's goodness of fit, accounting for the number of predictors. The F-statistic was found to be 7263.69, with 15 and 10,361 degrees of freedom (DF), and a p-value less than 2.22e–16, indicating that the model is highly statistically significant. These statistics highlight the robustness of the model, with the high R-squared suggesting that it effectively captures the factors influencing efficiency, and the p-value reinforcing the statistical significance of the findings. The final estimated equation is as follows:

$$\begin{aligned} Efficiency = {} & 0.28 + (0.02 \times CAACTA) + (0.71 \times FICITA) + \\ & + (0.72 \times CFNCOTA) + (0.02 \times DOITA) - \\ & - (0.16 \times DITA) - (0.03 \times TETA) - (0.05 \times IRR) + \epsilon. \end{aligned} \tag{12}$$

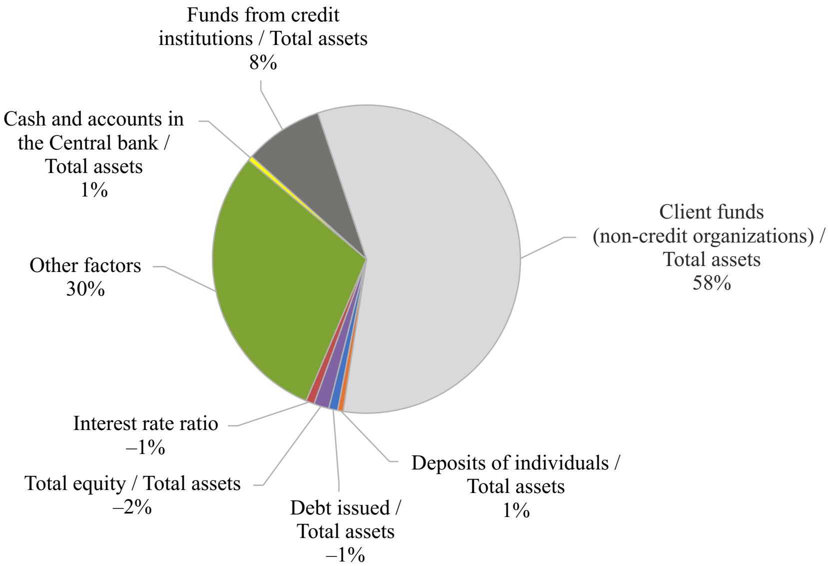

Fig. 3. Regression equation illustrating the impact of independent variables on Russian bank efficiency, 2000–2023.

Source: Author's calculations.

Fig. 3 presents the regression equation resulting from the analysis, which illustrates the impact of independent variables on the efficiency of Russian banks. It can be observed that *CFNCOTA*, *FFCITA*, *CAACTA*, and *DOITA* positively affected the efficiency of Russian banks by 58%, 8%, 1%, and 1%, respectively. In contrast, *TETA*, *DITA*, and *IRR* had a negative effect on bank efficiency by 2%, 1%, and 1%, respectively. The analysis also shows that other factors and variables contribute positively to the efficiency of Russian banks, accounting for 30%.

These results generally indicate that the sources of funding, their cost, and financial leverage have the greatest impact on the efficiency of Russian banks. Banks typically rely on deposits as the primary source of financing, as they are considered the least costly. Therefore, the significant positive effect of deposits on the efficiency of Russian banks, especially Client funds (non-credit organizations), can be observed. These deposits are generally seen as a stable and low-cost source of funding, and banks' heavy reliance on such a low-cost source enhances their efficiency. Moreover, accounts from credit institutions also have a positive impact on efficiency, as they provide flexible and efficient funding for short-term operations or to cover liquidity gaps. Thus, increasing reliance on these two sources, alongside the ability to manage a mix of stable and flexible low-cost financing, and investing it in productive assets that yield returns higher than the financing costs, contributes to improving the efficiency of Russian banks.

In contrast, there is a negative impact of issued debt and equity on efficiency, as these represent high-cost funding sources. Banks resort to these sources when they are unable to obtain low-cost alternatives. A high equity-to-assets ratio reflects reduced efficiency due to excessive reliance on private capital and poor use of financial leverage. Therefore, banks need to gradually increase financial leverage, but by using low-cost funding sources that do not include issued debt.

4.2.1. Characteristics of Russian banks by key performance-influencing variables

In this section, we aim to identify the characteristics of Russian banks based on key variables affecting their efficiency, with an impact greater than 1%, as determined in the previous section. These include three important variables: Client funds (non-credit organizations) / Total assets (58%), Funds from credit institutions / Total assets (8%), and Total equity / Total assets (–2%).

Fig. 4 presents these variables and their levels in Russian banks based on their efficiency, size, and ownership type. Regarding efficiency, it can be observed that as the proportion of Client funds (non-credit organizations) to total assets and the proportion of Funds from credit institutions to total assets increase, the efficiency of banks improves. Conversely, as the equity-to-assets ratio decreases (i.e., financial leverage increases), the efficiency of banks rises.

Regarding the efficiency of Russian banks based on their asset size, the study categorizes banks into four groups: mega banks (greater than 1 trillion and 50 billion rubles), large banks (ranging from 100 billion to 1 trillion 50 billion rubles), medium banks (ranging from 10 billion to 99.9 billion rubles), and small banks (less than 10 billion rubles).

Fig. 4 presents the key financial ratios that influence the efficiency of Russian banks, categorized by asset size. Russian mega banks are the most efficient, with an average efficiency rate of 74.6%. Although they receive a lower proportion of funds from credit institutions compared to banks of other sizes, mega banks compensate for this with a higher share of customer funds (from non-credit

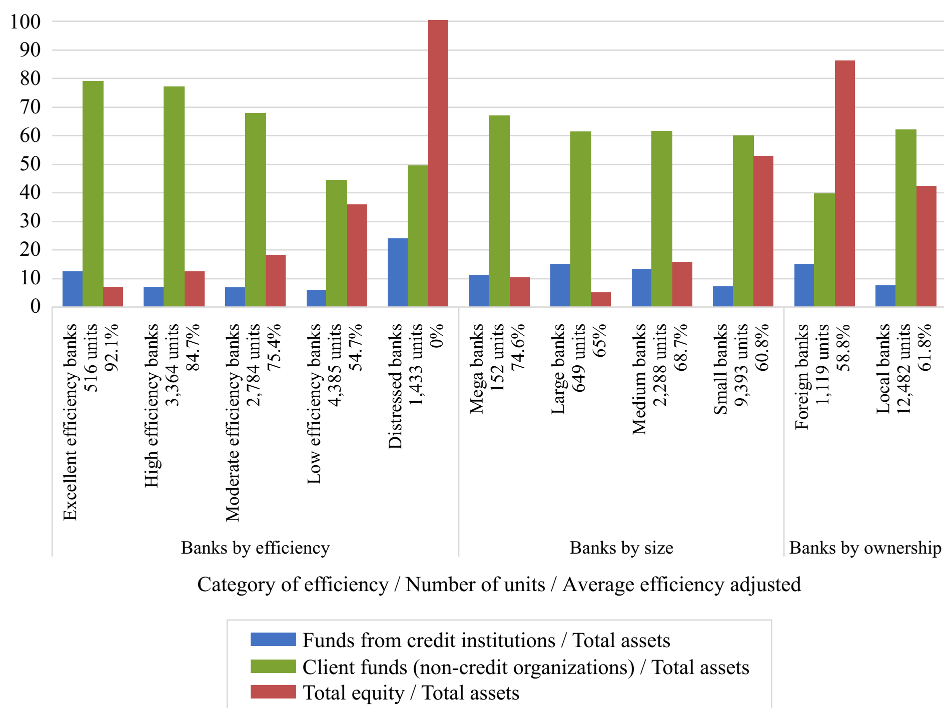

Fig. 4. Levels of key variables in Russian banks based on efficiency, size, and ownership type, 2000–2023 (%).

Source: Author's calculations.

organizations), which are lower-cost and more stable. This has positively impacted their efficiency, making them more efficient than other banks.

Fig. 4 shows that the equity-to-total assets ratio (leverage) in banks with excellent efficiency is 7%. The figure also indicates that the equity-to-total assets ratio (leverage) in mega banks is 10%, while in small banks, it reaches 52.9%, which is excessively high (low leverage). The ideal ratio should be 7%. In contrast, this ratio stands at 5% for large banks and 6% for medium banks, both of which are lower than the ideal level (high leverage).

Despite their relatively low leverage, mega banks remain the most efficient compared to other banks, with an efficiency level of 74.6%, which is considered moderate based on the classification used in this study. If mega banks aim to further enhance their efficiency, they need to reach 80%. This can be achieved by increasing leverage and assuming higher risks. While mega banks currently maintain low leverage to hedge against risks, they have the potential to raise it to 7%, which would improve their efficiency further. However, this remains contingent on their risk management strategy. This represents a strategic decision in the context of the current unstable economic conditions—either accept higher risks to boost efficiency or remain on the safer side. Regardless of this decision, mega banks continue to be the most efficient in Russia.

Large banks also face efficiency challenges, with medium and mega banks demonstrating higher efficiency. This is primarily due to the higher cost of raising funds, as large banks rely more on financing from credit institutions than other banks. To compensate, they attempt to increase their leverage levels to 5%. However, this strategy proves ineffective, as the increased risk does not translate into higher returns. Consequently, large banks expose themselves to leverage risks greater than the ideal 7% ratio, making them less efficient than medium and mega banks.

Regarding medium banks, they have achieved an efficiency level of 68.7%, which is also classified as low efficiency in this study. However, their efficiency is still higher than that of large and small banks, ranking second after mega banks in terms of efficiency. The efficiency of medium banks is close to a moderate level, and they need to raise it to 70% to be classified as moderately efficient. Medium banks have managed to improve their efficiency by increasing leverage to 6%, indicating that they manage leverage well, unlike large banks. However, medium banks should not further increase leverage to enhance efficiency, as their leverage is already high. Instead, they should adopt marketing strategies aimed at attracting more deposits from individuals and non-credit organizations.

Small banks face a significant challenge with their equity-to-assets ratios, as this ratio is exceptionally high at 53%. This indicates very low leverage and reliance on high-cost funding sources, which negatively impact their efficiency, resulting in an efficiency level of only 60.8%—the lowest among all banks—placing them at a higher risk of financial distress. This ratio in small banks is considered unreasonable and should not be present in banks. This large ratio does not reflect proper risk hedging but rather weak competitiveness and their inability to attract low-cost deposits. Therefore, small banks must improve their efficiency to at least 70% to reach a moderate level and move away from the danger zone.

Regarding the efficiency of Russian banks based on ownership type (domestic vs. foreign), Fig. 4 clearly illustrates the greater ability of domestic banks to attract low-cost deposits from non-credit institutions, along with their higher leverage levels compared to foreign banks. In contrast, foreign banks primarily rely on equity financing, which is a more expensive source of funds. This difference results in lower efficiency levels for foreign banks. Consequently, the average efficiency of Russian domestic banks is 61.8%, while that of foreign banks is 58.8%.

4.3. Projecting Russian bank efficiency trends (2024–2026) using Monte Carlo simulation

In this section, the Monte Carlo simulation methodology is used to estimate the future trends of Russian banks efficiency. The simulation predicts the expected changes in the independent variables affecting banking efficiency and evaluates their impact on the banking sector as a whole. Fig. 5 illustrates the values of the independent variables and the potential changes in these variables until the end of 2026, along with the equations for the trendlines that were adopted.

Through the analysis of the probabilities of different scenarios for each independent variable and the estimation of the outcomes for these scenarios from 2024 to 2026, the results presented in Table 2 were obtained. This table shows the Monte Carlo simulation results, indicating the most likely scenarios for each year and the expected adjusted efficiency percentage.

The results in Table 2 show that interest rates are expected to continue rising in the coming years due to the instability of the local currency (the ruble) and the high inflation rates caused by the Russia–Ukraine conflict. This increase in interest rates will lead to a noticeable rise in the volume of cash and bank accounts at the central bank.

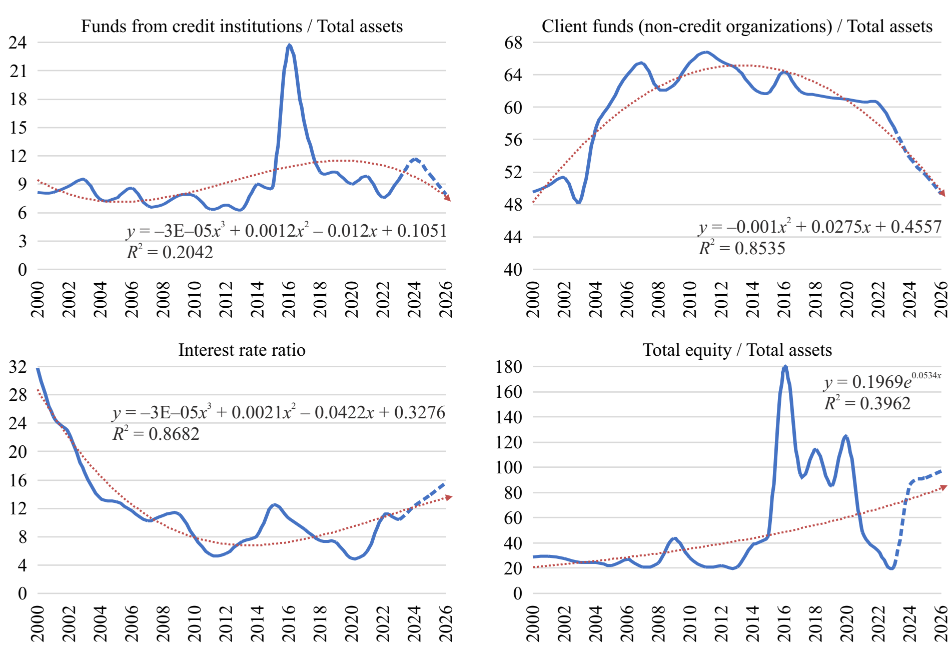

Fig. 5. Projected changes in independent variables affecting Russian bank efficiency based on trendline fitting and IQR-based outlier adjustment, 2020–2026 (%).

Source: Author's calculations.

Table 2
Monte Carlo simulation results for projected scenarios and adjusted efficiency estimates, 2024–2026 (%)

Variable	2023	2024	2025	2026
CAACTA	13.1	28.2	31.9	39.4
FFCITA	9.4	47.5	47.6	48.1
CFNCOTA	57.5	48.8	51.0	47.8
DOITA	25.6	43.3	42.3	43.2
DITA	0.8	40.5	41.5	41.8
TETA	21.4	52.4	50.9	51.0
IRR	10.4	12.5	13.5	15.5
Distressed banks ratio	13.7	24.2	22.2	19.6
Adjusted efficiency ratio	60.9	56.2	58.4	59.5
Probability of occurrence		4.1	3.6	3.8
Number of cases	359	406	363	381

Source: Author's calculations.

The forecasts also indicate significant changes in Client funds (non-credit organizations), which are expected to decline in 2024, then temporarily increase in 2025, before falling again in 2026. This reflects a state of instability caused by the poor performance of companies or the transfer of their funds and operations abroad due to economic sanctions. In contrast, the simulation shows a significant rise in Funds from credit institutions, which are expected to reach 48% in the coming years. This trend is logical given the anticipated decline in Client funds (non-credit organizations), especially in light of the current political and economic conditions.

The simulation results also show an upward trend in equity and issued debt, reflecting banks' increasing reliance on high-cost funding sources due to difficulties in acquiring Client funds (non-credit organizations). These changes are expected to lead to a decline in operational efficiency and revenues, with a significant increase in default rates, particularly among small and large banks that face considerable challenges in covering high costs of acquiring funds. These results highlight the impact of current economic and political factors on banking efficiency, underscoring the importance of adopting effective strategies to address these challenges. Fig. 6 illustrates the efficiency of Russian banks during the study period and the expected trends in the coming years.

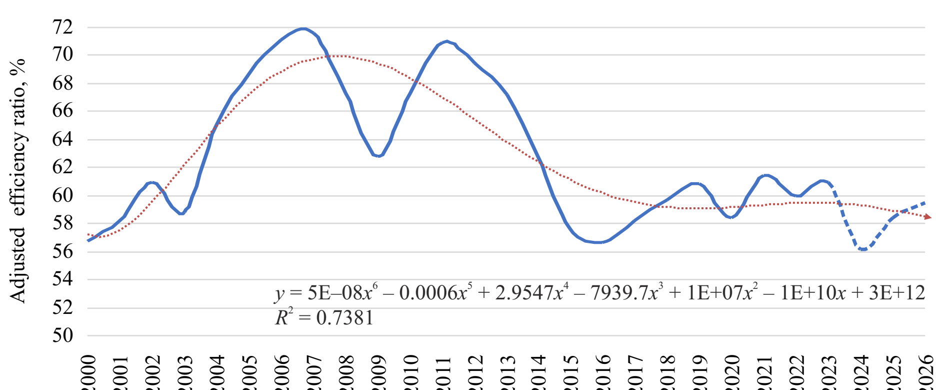

Fig. 6. Efficiency of Russian banks and projected future trends, 2000–2026.

Source: Author's calculations.

5. Conclusions and recommendations

5.1. Conclusions

This study aimed to assess the efficiency of Russian banks and identify the factors influencing it based on their size and ownership type while creating an efficiency metric and forecasting the future performance of the banks. The study relied on data from 680 Russian banks over the period from 2000 to 2023, employing DEA to measure technical efficiency using an input-oriented model and VRS technology. Additionally, panel data analysis was used to identify the variables affecting efficiency through a fixed-effects model, along with Monte Carlo simulations to forecast future performance for the period 2024 to 2026.

The results showed that Russian banks achieved the highest efficiency levels in 2006, 2007, and 2011, while the lowest efficiency levels were recorded in 2000, 2015, and 2016. There was a general downward trend in efficiency over time due to economic and political crises, particularly those related to oil prices and sanctions. The study indicated that higher ratios of non-credit organization deposits and funds from credit institutions to total assets, along with lower equity-to-assets ratios (higher leverage), were associated with higher efficiency in Russian banks.

Regarding bank size, the study found that mega banks with assets exceeding 1.05 trillion rubles were the most efficient, thanks to their ability to attract lower-cost deposits. In contrast, large banks with assets ranging between 100 billion and 1.05 trillion rubles showed lower efficiency than both mega banks and medium banks, due to higher fundraising costs, as leverage did not positively impact their performance. Medium banks with assets between 10 billion and 99.9 billion rubles ranked second in terms of efficiency, despite having lower leverage ratios compared to large and mega banks. On the other hand, small banks with assets under 10 billion rubles ranked the lowest in efficiency due to their heavy reliance on costly self-funding sources.

Regarding ownership, the study demonstrated that domestic Russian banks were more efficient than foreign banks, as they had the ability to attract lower-cost deposits and higher leverage ratios. In contrast, foreign banks relied on more expensive funding sources, negatively affecting their efficiency levels.

The study concluded that funding sources, cost structure, and leverage are the most influential factors affecting the efficiency of Russian banks.

The study forecasted that high interest rates would continue in the coming years due to currency instability and high inflation rates resulting from the Russia–Ukraine conflict. It also predicted significant changes in non-credit organization deposits, with an expected decline in 2024, a temporary rise in 2025, and a return to a decrease in 2026, reflecting instability caused by poor corporate performance or capital outflows due to economic sanctions. Additionally, an upward trend in equity and issued debt was anticipated, reflecting banks' increased reliance on high-cost funding sources due to difficulties in attracting non-credit organization deposits. These changes could lead to lower operational efficiency and higher default rates, especially among small and large banks, which face significant challenges in covering high fundraising costs.

5.2. Recommendations

Large banks should reduce leverage and develop more effective risk management strategies, as their high leverage does not positively impact efficiency, indicating potential weaknesses in credit or risk management.

If mega banks aim to enhance their efficiency to a higher level, they can do so by increasing leverage and taking on higher risks of up to 7%. However, this is a strategic decision in the current unstable economic conditions — either accept higher risks to improve efficiency or stay on the safer side. Regardless, mega banks remain the most efficient in Russia.

Small banks face a significant challenge regarding equity-to-asset ratios, as their low leverage results in costly funding sources, which substantially reduce their efficiency and increase the risk of default. To compete and survive, they must significantly boost their leverage by implementing marketing strategies aimed at attracting deposits from less expensive non-credit organizations. However, the critical question remains: Can small banks effectively increase their leverage? The answer is largely no, as they struggle with weak competitiveness and difficulty securing low-cost deposits, forcing them to rely on more expensive funding sources. As a result, they have only one viable option — either merge with larger banks or eventually exit the market.

Consequently, the study urges the Bank of Russia to encourage and facilitate mergers between large and small banks to enhance efficiency and competitiveness. Their interests align: large banks need to reduce leverage, while small banks must increase it.

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