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Modeling The Performance Efficiency Indicators Of Commercial Banks Using The Generalized Method Of Moments (Gmm) Based On Panel Data

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Abstract: This article analyzes the determinants of the efficiency indicators (ROAA, ROAE, NIM) of Uzbekistan's commercial banks using the two-step system GMM method. Based on panel data from 10 commercial banks for 2020–2025, three models were estimated to assess the effects of bank size, capital, operating efficiency, non-performing loans, digital transformation, and macroeconomic factors. The results show that non-performing loans (NPL) and bank size (SIZE) are the strongest negative determinants, while digital transformation (DIGI) is the strongest positive determinant.

Keywords: commercial banks, efficiency, GMM, system GMM, panel data, ROAA, ROAE, NIM, digital transformation, non-performing loans.

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1. Introduction

In working with dynamic panel data, the endogeneity problem that arises when explanatory variables are correlated with the error term seriously affects the reliability of models assessing bank efficiency. The Generalized Method of Moments (GMM), aimed at resolving this problem, was first proposed by Hansen [1]; subsequently Arellano and Bond developed the “difference GMM” approach [2], and Blundell and Bond developed the “system GMM” approach [3]. Unlike methods such as ARDL that include lagged variables directly in the model, the GMM method directly resolves the endogeneity problem by also using these lagged values as internal instruments, while allowing unobserved individual bank characteristics (unobserved heterogeneity) to be controlled for.

The relevance of the topic lies in the fact that traditional regression methods cannot fully capture the dynamic and interdependent relationships among the factors determining the efficiency of Uzbekistan's commercial banks, since a bank's past level of efficiency also affects its current-period outcomes (persistence), which gives rise to an endogeneity problem. It is therefore methodologically necessary to use the GMM method, which provides consistent estimates under dynamic panel data conditions.

The literature provides extensive evidence on the empirical application of GMM frameworks to assess bank profitability. Goddard et al. analyzed bank profitability across European banking systems [4]. Athanasoglou et al. examined the micro- and macroeconomic determinants of bank returns using dynamic panels [5]. Dietrich and Wanzenried evaluated the drivers of net interest margins and profitability during crisis periods [6]. Tan and Floros [7], as well as Tan [8], comprehensively documented the impacts of risk, competition, and economic growth on multi-dimensional bank efficiency metrics.

In transition economies, Djalilov and Piesse analyzed the role of credit risk and market structures [9], while Yao, Haris, and Tariq evaluated the performance structures within developing financial institutions [10]. Furthermore, Al-Homaidi et al. applied advanced dynamic panels to banking industries [11], and Le and Ngo expanded the analysis cross-country to highlight the role of structural and digital factors [12]. These historical implementations underscore the growing trend of integrating digitization variables alongside standard bank-internal indicators like capitalization, scale efficiency, and asset quality, which serves as a firm foundation for modeling Uzbekistan's domestic banking performance.

The purpose of this article is to identify the factors affecting the efficiency of Uzbekistan's commercial banks using the two-step system GMM method and to verify the statistical validity of the models through diagnostic tests. To achieve this purpose, the following tasks were set: first, to systematize the theoretical foundations of the GMM method and the differences between difference and system GMM; second, to construct separate dynamic panel models for three dimensions of efficiency (ROAA, ROAE, NIM); third, to resolve the endogeneity problem through the Forward Orthogonal Deviations transformation and instrument selection; fourth, to verify the diagnostic validity of the models through the Hansen and Arellano–Bond tests.

2. Research Methodology

The study applies the two-step system GMM method based on panel data from 10 commercial banks over 2020–2025 (six years). Although the observation period is shorter than in a number of other international studies, this is methodologically justified, since standardized and comparable data on Uzbekistan's commercial banks are available in full in the Orbis database precisely from 2020 onward, and because the system GMM method developed by Blundell and Bond is designed to yield consistent and efficient estimates even with a small T (time dimension) and a relatively larger N (number of cross-sections). ROAA, ROAE, NIM, CIR, asset size and ETA (Equity to Assets) indicators were obtained from the Orbis (Bureau van Dijk) database; inflation, NPL and DIGI indicators from the statistics of the Central Bank of the Republic of Uzbekistan [13]; and GDPG from the data of the State Statistics Committee. Here, ETA was used in place of the official capital adequacy ratio (CAR), since the Orbis database does not contain a risk-weighted assets indicator — a widely used alternative solution in the literature.

3. Results and Discussion

The Forward Orthogonal Deviations (FOD) transformation was applied to address the endogeneity problem of the dependent variable. Under the FOD transformation, the average of all future observations is subtracted from each bank's current observation, which eliminates time-invariant individual bank characteristics (such as management quality or market specialization) and leaves only the pure time-varying component to be estimated. The FOD transformation is more efficient than the traditional First Difference transformation under short time-period conditions such as $T = 6$, since it reduces data loss.

The lagged value of the dependent variable (lag1) was treated as endogenous, and its second- and third-period lagged values (lag2, lag3) were selected as internal instruments; the remaining independent variables were treated as exogenous, and their levels were also used as instruments — since levels and differences are used jointly, this is referred to as “system GMM.” Fourth and more distant lags were not selected, since under $T = 6$ an excessive number of instruments reduces the reliability of the Hansen test. To prevent the number of instruments from exceeding the number of banks ($N = 10$), the collapse method was applied, reducing the number of instruments from 19 to 11, which improved the reliability of the Hansen test results. Estimation was carried out in two steps: in the first step, initial estimates were obtained using a preliminary weighting matrix; in the second step, an optimal weighting matrix was constructed from the first-step residuals and the parameters were re-estimated, with standard errors corrected for small samples using the Windmeijer correction [15]. The three models take the following form:

$$ROAA_{it} = \alpha_1 \cdot ROAA_{it-1} + \beta_{1i} \cdot SIZE_{it} + \beta_{1j} \cdot ETA_{it} + \beta_{1k} \cdot CIR_{it} + \beta_{1l} \cdot NPL_{it} + \beta_{1m} \cdot DIGI_{it} + \gamma_{1i} \cdot GDPG_t + \gamma_{1j} \cdot INF_t + \mu_i + \varepsilon_{it}$$

$$ROAE_{it} = \alpha_2 \cdot ROAE_{it-1} + \beta_{2i} \cdot SIZE_{it} + \dots + \gamma_{2j} \cdot INF_t + \mu_i + \varepsilon_{it}$$

$$NIM_{it} = \alpha_3 \cdot NIM_{it-1} + \beta_{3i} \cdot SIZE_{it} + \dots + \gamma_{3j} \cdot INF_t + \mu_i + \varepsilon_{it}$$

Here i is the bank index ($i = 1, \dots, 10$); t is the year index ($t = 2020, \dots, 2025$); α is the coefficient on the lagged dependent variable; β are the coefficients on bank-internal factors; γ are the coefficients on macroeconomic factors; μ_i denotes unobserved individual bank characteristics; and ε_{it}

is the random error term. The models were verified using the Hansen over-identification test, the Arellano–Bond AR(2) autocorrelation test, and the eigenvalue stability condition [14]. Table 1 presents the results of the two-step system GMM model.

Table 1
Factors affecting the efficiency of Uzbekistan's commercial banks: two-step System GMM results (2020–2025)

Variable	ROAA	ROAE	NIM
lag1(Y)	0.0614	−0.0456	0.8464***
SIZE	−1.6904*	−13.2655***	−0.9073
ETA	0.1571	−0.2203	−0.0871
CIR	−0.0681**	−0.3547**	−0.0169
NPL	−0.5348***	−4.7719***	−0.0013
DIGI	0.9393*	7.7407***	0.4059
GDPG	0.4145	3.5298*	0.3132
INF	0.2051	2.4347***	0.2639**
Const	0.0847**	0.7524***	0.0073

*Source: calculated by the author in R. *p<0.05; **p<0.01; ***p<0.001.*

The results show that asset size (SIZE) has a significant negative effect on both ROAA (−1.690, $p<0.05$) and ROAE (−13.266, $p<0.001$) — indicating scale inefficiency among large banks, i.e., that as bank size increases, management becomes more complex and additional bureaucratic costs arise. The cost-to-income ratio (CIR) likewise has a statistically significant negative effect on ROAA (−0.068, $p<0.01$) and ROAE (−0.355, $p<0.01$), confirming the importance of cost-management efficiency. Non-performing loans (NPL) were found to have the strongest negative effect on both ROAA (−0.535, $p<0.001$) and ROAE (−4.772, $p<0.001$) — demonstrating that credit risk management is of decisive importance to bank efficiency.

Digital transformation (DIGI), meanwhile, proved to be the strongest positive determinant of both ROAA (0.939, $p<0.05$) and ROAE (7.741, $p<0.001$), a result indicating that the growing number of users of remote banking services increases profitability by reducing operating costs and expanding customer reach. GDP growth (GDPG) is positive and statistically significant in the ROAE model (3.530, $p<0.05$), confirming the positive effect of the macroeconomic environment on bank profitability, although this effect was not statistically significant in the ROAA and NIM models.

The NIM model, however, displays a different dynamic: the lagged value (lag1) shows high persistence (0.846, $p<0.001$), indicating that the net interest margin is strongly tied to its own past level, while bank-internal factors (SIZE, ETA, CIR, NPL, DIGI) had no statistically significant effect on NIM. Here inflation (INF) had a positive and statistically significant effect on NIM (0.264, $p<0.01$) — this result suggests that banks are able to maintain or increase their net interest margin during periods of inflation by repricing interest rates more quickly.

Taken together, the results of the three models show that bank-internal factors (especially NPL, SIZE and DIGI) more strongly affect overall profitability indicators such as ROAA and ROAE, while NIM is determined mainly by its own historical dynamics and by the macroeconomic factor of inflation. Table 2 presents the diagnostic test results for the three models.

Table 2
GMM model diagnostic test results

Indicator	ROAA	ROAE	NIM
Hansen test, p-value (H_0 : instruments exogenous)	0.305	0.914	0.840
Arellano–Bond AR(2), p-value	0.078	0.129	0.461
Eigenvalue modulus $ \lambda $ (stability condition: $ \lambda <1$)	0.061	0.046	0.846

Source: calculated by the author in R.

All three models passed the diagnostic tests successfully: Hansen test p-values above 0.05 confirmed the exogeneity of the instruments; the Arellano–Bond AR(2) test results confirmed the absence of second-order autocorrelation in the residuals; and the eigenvalue modulus values (all below the unit circle) confirmed the dynamic stability of the models.

4. Conclusion

According to the results of the two-step system GMM analysis, credit risk (NPL), bank size (SIZE), operating efficiency (CIR) and digital transformation (DIGI) were identified as the strongest determinants of the efficiency of Uzbekistan's commercial banks, with non-performing loans being the strongest negative factor and digital transformation the strongest positive factor. All three models (ROAA, ROAE, NIM) successfully passed the Hansen, Arellano–Bond AR(2) and eigenvalue stability tests, confirming their statistical validity and dynamic stability. At the same time, unlike ROAA and ROAE, the NIM indicator was found to be determined mainly by its own historical dynamics and by inflation — showing that different dimensions of bank efficiency are shaped by different sets of factors.

The following recommendations are proposed: (1) banks should strengthen credit-risk management systems and introduce early-warning mechanisms; (2) large banks should improve operational management and intensify measures aimed at reducing the CIR ratio in order to address scale inefficiency; (3) investment in digital banking services should be expanded, since this factor was found to be the strongest positive determinant of profitability; (4) strategic planning should be improved to account for the effects of macroeconomic factors (inflation, GDP growth); (5) future research is recommended to extend the observation period and include additional banks in the sample to improve the generalizability of the results.

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