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Econometric Analysis of the Factors Affecting the Performance Efficiency of Uzbekistan's Commercial Banks Using the Ardl Model

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Abstract: This article analyzes the internal and macroeconomic factors affecting the efficiency (ROA) of Uzbekistan's commercial banks using the Autoregressive Distributed Lag (ARDL) model. Based on monthly data for 2020–2025 (72 observations), the effects of capital adequacy, the share of non-performing loans, bank size, inflation and liquidity are estimated. The bounds testing results confirmed the existence of long-run cointegration. According to the long-run equation, non-performing loans were identified as the factor with the strongest negative effect on ROA.

Keywords: Commercial banks, ROA, ARDL model, bounds testing, cointegration, error correction model (ECM), capital adequacy, non-performing loans, liquidity.

1. Introduction

The stability and profitability of the banking system depend on numerous internal and external factors, and modern econometric methods are widely used to identify them. One widely applied approach in econometric analysis is the Autoregressive Distributed Lag (ARDL) model, first proposed by Pesaran and co-authors [1]. The main advantage of the ARDL model is that it can work with series integrated of order I(0) and I(1) and yields efficient results even for small samples.

A substantial body of empirical research has examined the internal and external determinants of commercial bank profitability. Athanasoglou et al. classified these determinants into bank-specific, industry-specific and macroeconomic factors, and found positive effects of capital adequacy and bank size together with a negative effect of non-performing loans [2]. Ben Naceur and Omran examined the effects of the regulatory framework, competition and macroeconomic conditions on commercial bank performance and found that inflation and interest rates significantly affect banks' financial results [3]. Dietrich and Wanzenried identified significant effects of capital adequacy, bank size and risk indicators on bank profitability, results that support the choice of variables applied in the present study [4]. Bordeleau and Graham, and Pasiouras and Kosmidou, empirically confirmed that the relationship between liquidity and bank profitability is complex in nature, in particular that an optimal level of liquidity exists beyond which additional liquidity no longer improves returns. More recent applications of the ARDL bounds-testing framework to Jordanian, Turkish and BRICS banking sectors have likewise confirmed long-run cointegration between profitability and its bank-specific and macroeconomic determinants. This body of literature shows that the ARDL model is one of the principal tools used to assess bank performance efficiency; however, research

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applying it comprehensively to Uzbekistan's commercial banks — including the stationarity, lag-selection, bounds-testing and ECM stages — has not been sufficiently conducted, which defines the scientific novelty of this article [5].

The relevance of the topic lies in the fact that the profitability indicators of Uzbekistan's commercial banks have fluctuated considerably over the years, and it has not yet been sufficiently studied which internal factors (capital, credit quality, size) and which external factor (inflation) these fluctuations are related to, nor how quickly the system returns to equilibrium following external shocks. To fill this gap, the ARDL model, which allows short-run and long-run dynamics to be estimated simultaneously, was applied.

The purpose of this article is to identify the internal and macroeconomic factors affecting the performance efficiency (ROA) of Uzbekistan's commercial banks using the ARDL model, to test for long-run equilibrium relationships, and to assess the speed at which the system returns to equilibrium after external shocks [6]. To achieve this purpose, the following tasks were set: first, to test the stationarity of the variables using the ADF test; second, to select the optimal ARDL specification based on information criteria (AIC, HQIC, SBIC); third, to verify the statistical validity of the selected model through diagnostic tests; fourth, to determine the existence of cointegration through the bounds testing approach and to estimate the speed of return to equilibrium through the error correction model (ECM) [7].

2. Methodology

Return on assets (ROA) was selected as the dependent variable, and capital adequacy (CAR), the share of non-performing loans (NPL), bank size (SIZE, in log form), the consumer price index (INI) and the liquid assets ratio (LIQ) were selected as independent variables. The data were compiled on a monthly basis for 2020–2025 (72 observations in total) based on the statistical bulletin of the Central Bank of the Republic of Uzbekistan.

Table 1. Description of the variables used in the model.

Variable	Symbol	Calculation formula	Unit of measure
Return on assets	ROA	(Pre-tax net profit / Total assets) × 100%	%
Capital adequacy	CAR	(Capital / Risk-weighted assets) × 100%	%
Share of non-performing loans	NPL	Non-performing loans / Total loans × 100%	%
Consumer price index	INI	(CPI _t – CPI _{t-1}) / CPI _{t-1} × 100%	%
Liquid assets ratio	LIQ	Liquid assets / Short-term liabilities × 100%	%
Bank size	SIZE	ln(Total assets)	log

Source: compiled by the author based on the statistical bulletin of the Central Bank of the Republic of Uzbekistan.

The ARDL model is built on time series and includes lagged values of the dependent variable as well as current and lagged values of the independent variables. Its general form is as follows:

$$Y_t = \alpha + \sum_{i=1}^p \beta_i Y_{t-i} + \sum_{j=0}^q \gamma_j X_{t-j} + \varepsilon_t$$

The model proposed for the study takes the following form:

$$ROA_t = \alpha + \beta_1 ROA_{t-1} + \beta_2 CAR_t + \beta_3 NPL_t + \beta_4 SIZE_t + \beta_5 INI_t + \beta_6 LIQ_t + \varepsilon_t$$

Before applying the ARDL model, the stationarity of each variable was tested using the Augmented Dickey–Fuller (ADF) test where H_0 is that the series contains a unit root (is

non-stationary) and H_1 is that the series is stationary. Table 2 presents the ADF test p-values at the level, $I(0)$, and first-difference, $I(1)$, and the resulting order of integration for each variable.

Table 2. Stationarity of the time series (ADF test).

Nº	Variable	ADF I(0)	p-value: ADF I(1)	p-value: ADF I(1)	Order of integration
1	Return on assets (ROA)	0.0008	—	—	$I(0)$
2	Capital adequacy (CAR)	0.0001	—	—	$I(0)$
3	Share of non-performing loans (NPL)	0.2999	0.0000	0.0000	$I(1)$
4	Consumer price index (INI)	0.0000	—	—	$I(0)$
5	Liquid assets ratio (LIQ)	0.2767	0.0000	0.0000	$I(1)$
6	Bank size (SIZE)	0.4575	0.0000	0.0000	$I(1)$

Source: calculated by the author in Stata.

The results in Table 2 show that ROA, CAR and INI were stationary at the level, $I(0)$, while NPL, LIQ and SIZE became stationary only after first-differencing, $I(1)$. All variables are stationary at either $I(0)$ or $I(1)$, and no $I(2)$ variable was found — confirming that the condition required for applying the ARDL model is satisfied.

Once stationarity was confirmed, information criteria (AIC, HQIC, SBIC) based on a VAR model were applied to determine the optimal lag length for the model. Table 3 presents the results of these criteria for lags 0 through 4.

Table 3. Lag-selection criteria for constructing the ARDL model.

Lag	LL	LR	AIC	HQIC	SBIC
0	-437.332	—	13.039	13.117	13.235
1	-28.278	818.110***	2.067*	2.610*	3.438*
2	-2.881	50.794	2.379	3.388	4.925
3	23.794	53.349*	2.653	4.127	6.374
4	60.412	73.237*	2.635	4.575	7.531

*Source: calculated by the author in Stata. * $p < 0.05$; *** $p < 0.001$.*

According to Table 3, the lag-selection criteria (AIC, HQIC, SBIC) based on the VAR model statistically identified lag 1 as optimal. However, in order to more fully capture the lagged effects of economic processes, the maximum lag length was set at 2, since the optimal lag identified through the VAR model is applied as an upper bound for the ARDL model. This approach allowed short-run and lagged effects to be jointly accounted for without unnecessarily complicating the model.

Within the identified lag bound, various ARDL model combinations were constructed following the standard ARDL cointegration procedure and the most optimal specification was selected through diagnostic tests (Breusch–Godfrey, heteroskedasticity, Ramsey RESET, CUSUM); the existence of cointegration was then tested using the bounds testing approach of Pesaran, Shin and Smith and the error correction model (ECM) was constructed.

3. Results

The dynamics of the time series are presented in Figure 1. As shown, bank size grew steadily, while ROA exhibited considerable fluctuation with no stable trend observed. Non-performing loans rose initially but were subsequently reduced, indicating an improvement in credit quality [8].

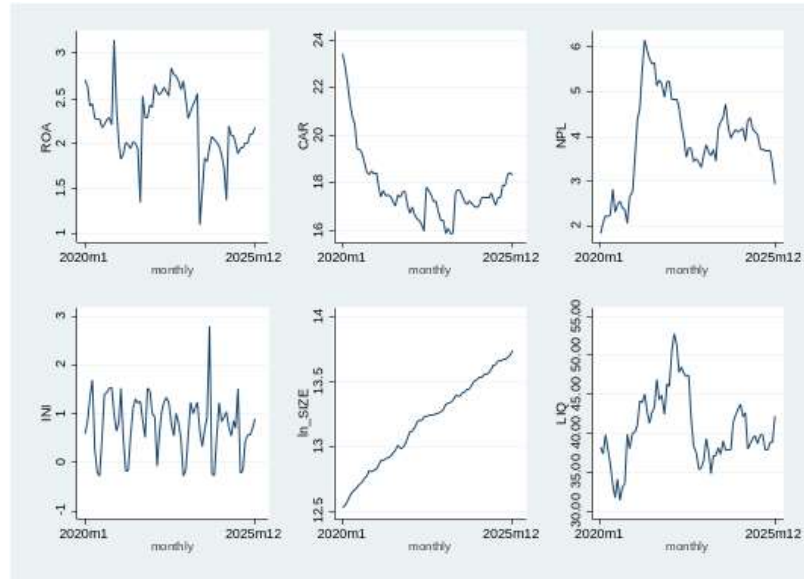


Figure 1. Time series dynamics (ROA, CAR, NPL, INI, ln_SIZE, LIQ)

Table 4 presents the five ARDL model combinations developed during the study and their evaluation criteria.

Table 4. ARDL model combinations and their evaluation criteria.

Indicator	Model 1	Model 2	Model 3	Model 4	Model 5
L1.ROA	0.486***	0.464***	0.515***	0.346**	0.353**
CAR	-0.078	-0.039	-0.072	-0.099*	-0.097*
NPL	-0.088	-0.149*	-0.085	-0.200**	-0.195**
SIZE	-0.260	—	-5.189*	-0.322*	-0.312*
LIQ	—	-0.027	—	-0.027	-0.027
R-squared	0.431	0.503	0.468	0.548	0.546
AIC	28.515	20.935	27.709	18.187	16.430
BIC	39.829	34.511	43.548	36.289	32.269

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

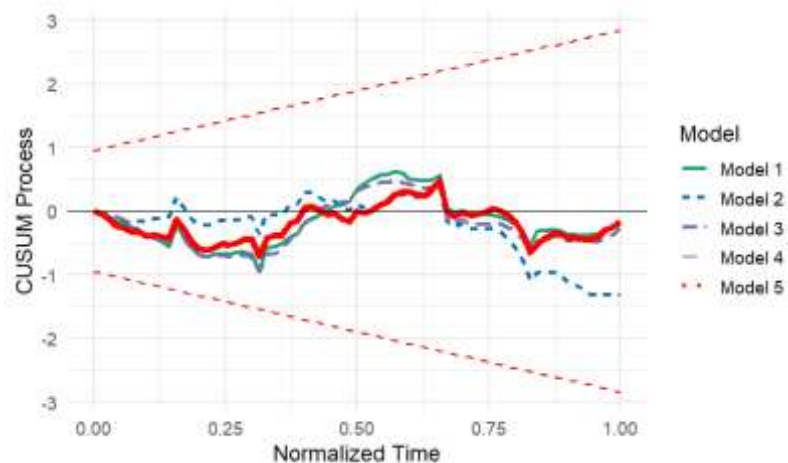
Table 4 shows that among the models examined, Model 4 and Model 5 are the most efficient and statistically optimal in terms of overall goodness-of-fit criteria. Although Model 4 has higher explanatory power ($R^2 = 0.548$), Model 5 is preferred by the BIC criterion (BIC = 32.269 versus 36.289). To make a final choice among the models, diagnostic tests examining the statistical properties of the residuals were conducted; their results are presented in Table 5 [9].

Table 5. Results of tests for the adequacy of the ARDL model (diagnostic tests, p-values).

Test	Model 1	Model 2	Model 3	Model 4	Model 5	Condition
Breusch–Godfrey	0.763	0.789	0.892	0.627	0.584	$p > 0.05$
Heteroskedasticity	0.619	0.346	0.235	0.322	0.347	$p > 0.05$
Ramsey RESET	0.018	0.444	0.202	0.481	0.417	$p > 0.05$
CUSUM	0.460	0.723	0.444	0.772	0.775	$p > 0.05$

Source: calculated by the author in Stata.

The results in Table 5 show that no autocorrelation (Breusch–Godfrey) or heteroskedasticity problems were found in the residuals of any of the five models. However, the Ramsey RESET test indicated a specification error in Model 1 ($p = 0.018 < 0.05$), while the remaining four models passed this test successfully [11]. Taking the diagnostic tests (Breusch–Godfrey, heteroskedasticity, Ramsey RESET, CUSUM) and the information criteria together, Model 5 was ultimately selected as the optimal model on all criteria [10]. Figure 2 presents the results of the CUSUM parameter-stability test for all models in graphical form — no model's line crosses the critical bounds, indicating the absence of structural change. Model 5's line, in particular, shows relatively lower-amplitude fluctuations, confirming its higher parameter stability [11].

**Figure 2.** Parameter stability assessment of the ARDL models (CUSUM test).

Once the optimal model (Model 5) was identified, the bounds testing approach developed by Pesaran, Shin and Smith was applied to test for the existence of a long-run equilibrium relationship among the variables. Table 6 presents the test results together with the corresponding critical bound values.

Table 6. Cointegration (bounds testing) results.

Significance level	I(0) bound	I(1) bound
10%	2.548	3.669
5%	3.029	4.255
1%	4.112	5.548

H_0 : no cointegration; computed F -statistic = 7.215 ($p = 0.0008$).

The results in Table 6 show that the computed F -statistic (7.215) exceeds even the upper bound at the 1% significance level ($I(1) = 5.548$), providing grounds to reject the null hypothesis even at the 1% significance level — that is, the existence of long-run

cointegration among the variables of Model 5 was strictly confirmed statistically. The long-run equation was as follows:

$$ROA = 10.68 - 0.150 CAR - 0.301 NPL - 0.482 SIZE + 0.043 LIQ$$

Discussion

According to the long-run equation, capital adequacy (CAR), the share of non-performing loans (NPL) and bank size (SIZE) have a negative effect on ROA, with the higher magnitude of the NPL coefficient indicating that non-performing loans are the strongest negative factor: a 1-percentage-point increase in CAR and NPL reduces ROA by 0.150 and 0.301 percentage points, respectively, while a 1% increase in bank size reduces ROA by approximately 0.0048 percentage points [12]. Liquidity (LIQ), by contrast, is positive and statistically significant, with a 1-percentage-point increase raising ROA by 0.043 percentage points — indicating that, in the long run, higher liquidity supports bank stability and profitability [13].

To assess the short-run dynamics and the mechanism by which the system returns to long-run equilibrium, an error correction model (ECM) was constructed:

$$\Delta ROA = 6.90 - 0.027 \Delta LIQ - 0.646 ECT_{t-1}$$

According to the ECM results, the error correction term (ECT) coefficient is -0.646 , negative and statistically significant ($p = 0.000$) — indicating that approximately 64.6% of any deviation arising in the system is corrected each month, meaning that the banking system returns to its long-run equilibrium within about 4–5 months following an external shock. The short-run change in liquidity (ΔLIQ) has a negative effect on ROA (a 1-percentage-point increase in liquidity reduces ROA by an average of 0.027 percentage points), but this effect is not statistically significant at the 5% level ($p = 0.077$), being only weakly significant at the 10% level. This result indicates that the effect of liquidity on bank profitability differs in nature between the short run and the long run [14].

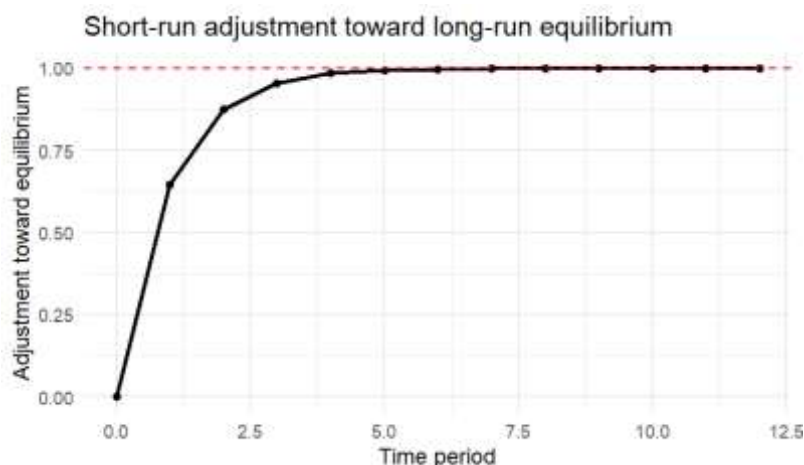


Figure 3. Dynamics of ROA's return to equilibrium (ECM).

As shown in Figure 3, short-run shocks arising in the banking system do not persist for long, and the system quickly returns to equilibrium through the error correction mechanism. In the figure, the black curve represents the short-run adjustment process, while the red dashed line represents the long-run equilibrium state. An important point in interpretation is that 'long run' here does not mean a period of several years, but rather the stable equilibrium state that forms once short-run fluctuations have been eliminated [15].

4. Conclusion

According to the results of the ARDL-based analysis, capital adequacy, the share of non-performing loans and bank size have a negative and statistically significant effect on the profitability (ROA) of Uzbekistan's commercial banks, while liquidity has a positive and statistically significant effect, with non-performing loans emerging as the strongest negative factor. The diagnostic tests and bounds testing results confirmed that the selected model is statistically valid and stable. The banking system is capable of returning to equilibrium within a relatively short period (4–5 months) following external shocks, indicating the banking sector's adaptability to external shocks.

The following recommendations are proposed: (1) strengthen effective credit-risk management and the methodology for assessing expected credit losses under IFRS 9 (2) improve measures aimed at reducing the share of non-performing loans; (3) maintain liquidity at an optimal level, since its short-run and long-run effects differ in nature; (4) improve operational management in large banks in order to address scale inefficiency; (5) given the banking system's relatively rapid (4–5-month) return to equilibrium, develop proactive rather than reactive adaptation strategies in response to monetary policy shocks.

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