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ECONOMETRIC ANALYSIS OF THE IMPROVEMENT OF CREDIT SERVICES

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A B S T R A C T

The quality of credit services and the level of non-performing loans (NPLs) are key determinants of financial stability and banking sector soundness. This study analyzes the main factors influencing the volume of NPLs in the banking sector of Uzbekistan through advanced econometric modeling. Using monthly data from January 2020 to January 2025 obtained from the Central Bank of the Republic of Uzbekistan, we examine the impact of capital adequacy, term deposits, liquidity indicators, and other key variables on NPL dynamics. Pearson correlation analysis is applied to identify significant relationships, followed by multiple regression estimation. Diagnostic checks reveal the presence of autocorrelation and heteroskedasticity in the static model, which is addressed through dynamic modeling using ARMAX and ARIMA specifications. The ARMAX(1,1) model demonstrates that capital adequacy has a negative and statistically significant impact on NPLs, whereas term deposits and liquidity ratios exert positive effects. The final ARIMA(0,1,0) model provides a robust baseline for short-term forecasting, indicating an expected monthly increase of 300.27 units in NPL volume. The findings emphasize the importance of strengthening capital adequacy, managing liquidity prudently, and ensuring controlled deposit growth to mitigate credit risk and enhance the quality of credit services in Uzbekistan's banking sector.

K E Y W O R D S

Non-performing loans (NPL); Credit risk; Banking sector; Econometric modeling; ARIMA; ARMAX; Capital adequacy; Term deposits; Liquidity ratio; Uzbekistan.

Introduction

Credit risk remains one of the most critical challenges to the stability of the banking sector. A high level of non-performing loans (NPLs) not only undermines banks' balance sheets and profitability but also weakens the overall financial system, limiting credit growth and slowing economic development. In many countries, NPL dynamics are closely linked to macroeconomic conditions and banking system indicators, including capital adequacy, deposit structure, and liquidity ratios. Strengthening credit quality is therefore essential for maintaining financial stability, especially in emerging economies.

In recent years, Uzbekistan has experienced rapid financial sector development characterized by expanding credit portfolios, growing deposit bases, and evolving liquidity management practices. These changes have increased the importance of monitoring credit risk and understanding the factors driving NPLs. Drawing on international best practices, this study applies econometric modeling techniques to evaluate the relationship between NPLs and key financial stability indicators in the Uzbek banking sector. By integrating both static and dynamic modeling approaches, the research seeks to provide evidence-based recommendations for strengthening credit service quality and supporting sustainable banking sector growth.

2. Literature Review / Analysis

The concept of credit has long been recognized as a fundamental economic category. Abdullaev Yo. et al. define a loan as a relationship arising from the borrowing and repayment of temporarily available funds with remuneration over a specified period. This relationship involves two parties: the lender (creditor) and the borrower (debtor), forming the foundation of modern credit markets [1].

Rashidov U. et al. further describe credit as a set of economic relations tied to the borrowing and repayment of funds, emphasizing its structured, economic—not merely social—nature [2].

L. Krolevetskaya highlights that credit emerged historically after the introduction of money, accelerating economic activity by enabling the time-shifting of consumption and investment [3].

Abdullayeva Sh. and Azizov underscore the contractual basis of credit transactions: borrowers are obliged to repay borrowed funds within a fixed period along with additional remuneration [4].

At the macro level, O. Sattarov notes that the loan-to-GDP ratio is a critical indicator of investment orientation and financial sector depth, with higher ratios typically associated with stronger economic growth and financial intermediation [5].

Together, these perspectives establish credit as both a microeconomic and macroeconomic driver of development. Understanding its dynamics is crucial for analyzing credit risk, NPL trends, and the stability of banking systems—particularly in developing economies such as Uzbekistan.

3. Data and Methodology

This study is based on monthly time-series data for the period **January 2020 – January 2025,** collected from the Central Bank of the Republic of Uzbekistan.

- **Dependent variable (Y)**: Volume of non-performing loans (NPL)
- **Independent variables:**
- X_1: Capital adequacy ratio (%)
- X_2: Volume of term deposits (billion UZS)
- X_3: Fixed capital (billion UZS)
- X_4: Highly liquid assets (billion UZS)
- X_5: Instant liquidity ratio (%)

The methodological framework consists of the following steps:
1. Correlation Analysis — Using the **Pearson correlation coefficient** to identify statistically significant linear relationships between NPLs and explanatory variables.
2. Multicollinearity Check — Exclusion of variables with strong mutual correlations (e.g., X2X_2X2 and X3X_3X3 correlation of 0.9872).
3. Static Regression Analysis (OLS) — Estimation of a baseline multiple linear regression model.
4. Diagnostic Testing — Application of the **Durbin–Watson statistic** to test for autocorrelation and **Breusch–Pagan test** for heteroskedasticity.
5. Dynamic Modeling (ARMAX) — Inclusion of lagged dependent variables to correct autocorrelation and capture temporal dynamics.
6. Forecasting (ARIMA) — Identification of the optimal ARIMA specification for NPL forecasts based on AIC and residual tests.

4. Results and Discussion

4.1 Correlation Analysis

Taking into account the specific characteristics of Uzbekistan's banking system, this study employs econometric methods to analyze the impact of several key indicators on the volume of non-performing loans (NPLs). The indicators considered include the overall capital adequacy ratio, the volume of term deposits, fixed capital, highly liquid assets, and the instant liquidity ratio.

The analysis is based on official data provided by the Central Bank of the Republic of Uzbekistan, which were used to assess how these economic indicators influence changes in the volume of NPLs in the banking sector. Based on the empirical results, corresponding forecasts were also developed.

Since improving the quality of credit services is directly linked to reducing the volume of non-performing loans, the monthly volume of NPLs for the period 2020–2025 was selected as the dependent variable, while the banking system stability indicators were chosen as independent variables.

To evaluate the relationships between these factors and NPL dynamics, the **Pearson correlation coefficient (r)** was applied to measure both the strength and direction of the correlations. This approach made it possible to identify the most statistically significant indicators affecting the level of non-performing loans in Uzbekistan's banking sector

Table 1. Analysis of the Correlation Between NPL and Banking System Indicators [1]

Correlation Relationship

Probability	NPL (Y)	Capital Adequacy Ratio (X_1)	Volume of Time Deposits (X_2)	Fixed Capital (X_3)	Highly Liquid Assets (X_4)	Instant Liquidity Ratio (X_5)
NPL - Y	1.000000					
Capital Adequacy Ratio (X_1)	-0,7764	1.000000				
Volume of Time Deposits (X_2)	0,8081	-0,5708	1.000000			
Fixed Capital (X_3)	0,8010	-0,5533	0,9872	1.000000		
Highly Liquid Assets (X_4)	0,8253	-0,6979	0,8905	0,8694	1.000000	
Instant Liquidity Ratio (X_5)	0,8451	-0,7674	0,6932	0,6864	0,8778	1.000000

[1] Calculated using Gretl software.

Based on the statistical table at the 5 percent significance level, the coefficients of the Pearson correlation (r) were found to be statistically significant. The correlation coefficients between NPLs and the selected indicators were as follows: capital adequacy ratio – –0.7764, volume of term deposits – 0.8081, fixed capital – 0.8010, highly liquid assets – 0.8253, and instant liquidity ratio – 0.8451.

When selecting explanatory variables for regression analysis, it is essential to ensure that these variables are not excessively correlated with each other. High levels of **multicollinearity** can distort estimation results and undermine the statistical reliability of the model. In particular, when the correlation between independent variables exceeds their correlation with the dependent variable, the precision and interpretability of the estimated coefficients may be compromised.

The correlation matrix reveals a clear multicollinearity problem among the selected indicators. Specifically, fixed capital (X_3)) exhibits a stronger correlation with the volume of term deposits (X_2) — 0.9872 — than with NPL itself. Likewise, highly liquid assets (X_4)) display stronger correlations with term deposits (0.8905) and fixed capital (0.8694) than with NPL.

Therefore, to mitigate multicollinearity and improve the robustness of the regression model, the indicators for fixed capital and highly liquid assets were excluded. Pearson correlation analysis was then repeated using the remaining variables to examine their relationship with the volume of non-performing loans. The updated results are presented in the following table.

Table 2 Analysis of the Correlation Between NPL and Banking System Indicators [2]

Корреляцион боғлиқлиги Эҳтимоллилик	NPL(Y)	Capital Adequacy Ratio (X_1)	Volume of Time Deposits (X_2)	Instant Liquidity Ratio (X_5)
NPL - Y	1.000000			
Capital Adequacy Ratio (X_1)	-0,7764	1.000000		
Volume of Time Deposits (X_2)	0,8081	-0,5708	1.000000	
Instant Liquidity Ratio (X_5)	0,8451	-0,7674	0,6932	1.000000

Based on the statistical table at the 5 percent significance level, the coefficients of the Pearson correlation (r) were found to be statistically significant. Accordingly, the correlations between NPLs and the respective indicators were determined as follows: capital adequacy ratio – –0.7764, volume of term deposits – 0.8081, and instant liquidity ratio – 0.8451.

4.2 Static Regression Model (OLS)

The general form of the multiple linear regression equation can be expressed as:

$$Y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_5 + \cdots + \beta_n x_n + \varepsilon_n$$

where:

[2] Calculated using Gretl software.

- α — — the constant term, representing the initial value of the dependent variable when all explanatory variables are zero;
- $\beta_1, \beta_2, \ldots \beta_n$ — — the regression coefficients that measure the magnitude and direction of the impact of each independent variable on the dependent variable;
- $x_1, x_2, \ldots x_n$ — the explanatory (independent) variables;
- ε_n — — the error term capturing unobserved factors that may influence the dependent variable.

Using the factors that exhibited significant correlations with NPLs, a probabilistic regression analysis was carried out to estimate the relationship between non-performing loans and the selected explanatory variables. This step allowed for quantifying the marginal effects of key banking indicators on NPL dynamics while controlling for potential noise in the data

Table 3 Regression Statistical Analysis of NPL and Its Influencing Factors (Model 1))[3]

Dependent Variable: NPL
Method: Least Squares
Sample (adjusted): 2020:01-2025:01 (T = 61)
Included observations 61

Variables	Coefficient	**Std. Error**	t- Statistic	Prob.
C	16552,0	6464,73	2,560	0,0131 **
Capital Adequacy Ratio (X_1)	−877,229	267,157	−3,284	0,0018 ***
Volume of Time Deposits (X_2)	0,0578580	0,0104818	5,520	8,67e-07 ***
Instant Liquidity Ratio (X_5)	98,1541	26,2621	3,737	0,0004 ***

R- squared	0,839672	S.D. of Dependent Variable	5683,958
Sum of Squared Residuals	3,11e+08	S.E. of Regression	2335,040
F(3, 57)	99,50674	**Adjusted R-squared**	0,831233
Log-likelihood	−557,5895	Prob(F-statistic)	1,24e-22
Schwarz Criterion (SC)	1131,623	Akaike Information Criterion (AIC)	1123,179
ρ (rho) parameter	0,881792	Hannan–Quinn Criterion (HQC)	1126,488
Mean of Dependent Variable	14712,60	Durbin–Watson Statistic	0,240215

Based on the regression statistical analysis of NPL and its influencing factors, the regression equation can be constructed as follows:

$$y = 16\,552 - 877{,}229 * x_1 + 0{,}0578 * x_2 + 98{,}1541 * x_5 + \varepsilon$$

[3] Calculated using Gretl software.

In this regression model, all the variables are statistically significant at the 5 percent significance level:

- Capital adequacy ratio ($p = 0.0018 < 0.005$),
- Volume of time deposits ($p = 8.67e{-}07 < 0.005$),
- Instant liquidity ratio ($p = 0.0004 < 0.005$).

This indicates that each of these factors has a significant impact on the volume of non-performing loans (NPL).

Specifically:

- A 1% increase in the capital adequacy ratio reduces the volume of non-performing loans by approximately 877.229 billion UZS;
- A 1 billion UZS increase in the volume of time deposits leads to an increase in non-performing loans by about 57.8 million UZS;
- A 1% increase in the instant liquidity ratio results in an increase in non-performing loans by approximately 98.1541 billion UZS.

Hence, the results suggest that while strengthening capital adequacy contributes to a reduction in credit risk, the growth in time deposits and higher liquidity levels may, under certain conditions, be associated with an increase in non-performing loans in the banking sector.

To determine the statistical reliability of the above model, the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC) were examined, along with tests for the presence of first- and second-order autocorrelation in the residuals.

Based on the 5 percent significance level from the Durbin–Watson statistical table, the condition for the absence of autocorrelation is considered to hold when $1.54 < DW < 2.46$.

From the regression results above, the Durbin–Watson statistic (DW) is 0.240215, which is far below the lower threshold of 1.54. This indicates the presence of strong positive autocorrelation between the residuals of the model.

In practical terms, this means that the residuals (errors) from one period are highly correlated with those from the next period — suggesting that important time-dependent dynamics may not have been fully captured by the model.

To address this issue, methods such as including lagged variables, applying autoregressive models (AR(1)), or using the Cochrane–Orcutt or Generalized Least Squares (GLS) correction procedures can be employed to reduce autocorrelation and improve the reliability of the regression estimates.

To test for the presence of heteroskedasticity in the residuals of the selected regression model, the Breusch–Pagan (BP) test is applied.

In this test, the null hypothesis (H_0) states that heteroskedasticity is not present — meaning that the residuals have constant variance (homoskedasticity).

The interpretation of the test results is as follows:

- If p-value > 0.05, we fail to reject H_0, indicating that heteroskedasticity is not present, and the model's random errors are homoskedastic.
- If p-value ≤ 0.05, we reject H_0, which implies that heteroskedasticity is present — the variance of the residuals is not constant, and this may affect the reliability of the estimated coefficients.

Thus, the Breusch–Pagan test helps to confirm whether the assumption of equal error variance holds for the selected regression model, ensuring the statistical robustness of the estimation results.

Table 4 Breusch–Pagan Test Results for the Selected Regression Model of NPL and Its Influencing Factors [4].

Breusch–Pagan Test Results for the Selected Regression Model (Second-Order Heteroskedasticity)
Method: Least Squares
Sample (adjusted): 2020:01-2025:01 (T = 61)
Dependent Variable: uhat

Variables	Coefficient	Std. Error	t-Statistic	Prob.
const	2,55504	3,26232	0,7832	0,4368
Capital Adequacy Ratio (X_1)	−0,120962	0,134816	−0,8972	0,3734
Volume of Time Deposits (X_2)	−1,60018e-05	5,28944e-06	−3,025	0,0037 ***
Instant Liquidity Ratio (X_5)	0,0232335	0,0132527	1,753	0,0850 *

Sum of Squared Residuals = 15,572

Test Statistic: LM = 7,785975,
Prob.= P(Хи-square (3) > 7,785975) = 0,050648
According to the results of the Breusch–Pagan test, since P < 0.13, it can be concluded that heteroskedasticity is present in the model, indicating that the residuals of the selected regression are not homoskedastic.
Therefore, considering that the chosen model did not pass the regression diagnostic tests satisfactorily, the forecast indicators derived from this model cannot be considered reliable.

4.3 ARMAX Model (1,1)

To ensure the statistical robustness of the model and to eliminate autocorrelation, the next step is to modify the model. For this purpose, a dynamic regression approach is applied by including the lagged dependent variable Y(t−1) as an explanatory variable, and the ARIMA model is employed.
If the initial model is…
$Y_t=\beta_0+\beta_1 X1_t+\beta_2 X2_t+\beta_3 X5_t+\varepsilon_t$
If the initial model was expressed in the following form, the new model — incorporating the lagged dependent variable — will take the following form:

$Y_t=\alpha_0+\alpha_1 Y_{t-1}+\alpha_2 X1_t+\alpha_3 X2_t+\alpha_4 X5_t+u_t$
As a result, the residuals u_t will exhibit less autocorrelation.

[4] Calculated using Gretl software.

Table 5 ARMAX Model (Model 2) for NPL and Its Influencing Factors[5]

Dependent Variable: NPL
Method: ARMAX
Sample (adjusted): 2020:01-2025:01 (T = 61)
Included observations 61

Variable	Coefficient	Std. Error	z	P-value
const	17875,7	6559,43	2,725	0,0064 ***
phi_1	0,870335	0,0695245	12,52	5,92e-036***
theta_1	0,152754	0,134101	1,139	0,2547
Capital Adequacy Ratio (X_1)	−768,170	289,136	−2,657	0,0079***
Term Deposits Volume (X_2)	0,0654652	0,0241074	2,716	0,0066 ***
Instant Liquidity Ratio (X_5)	50,1475	25,5143	1,965	0,0494 **
		Standard Deviation of Innovations		1030,483
Log-likelihood	−510,6050	**Standard Error of the Model**		5683,958
		Akaike Information Criterion		
Schwarz Criterion:	1049,986			1035,210
Mean of Innovations:	20,55437	**Hannan–Quinn Criterion**		1041,001
Mean of Dependent Variable:	14712,60			
	Real Part	**Imaginary Part**	**Modulus**	Frequency
Root (AR Part)	1,1490	0,0000	1,1490	0,0000
Root (MA Part)	-6,5465	0,0000	6,5465	0,5000

Based on the regression statistical analysis of NPL and its influencing factors, we can construct the regression equation according to the above model. The autoregressive model with a mean and exogenous variable component, ARMAX(1,1) (AutoRegressive Moving Average with eXogenous variables), takes the following form:

$$\mathbf{Y_t = 17\,875{,}7 + 0{,}8703 \cdot Y_{t-1} + 0{,}1528 \cdot \varepsilon_{t-1} - 768{,}17 \cdot X1_t + 0{,}0655 \cdot X2_t + 50{,}15 \cdot X5_t + \varepsilon_t}$$

where:

Y_t — the level of non-performing loans at time t;
Y_{t-1} — the volume of non-performing loans in the previous period
$X1_t$ — capital adequacy ratio at time;
$X2_t$ — volume of term deposits at time;
$X5_t$ — instant liquidity ratio at time;
ε_t — the stochastic error (shock) at time.

In this regression model, all explanatory variables — capital adequacy ratio ($p = 0.0079 < 0.05$), volume of term deposits ($p = 0.0066 < 0.05$), and instant liquidity ratio ($p = 0.0494 < 0.05$) — are statistically significant at the 5% significance level.

[5] Calculated using Gretl software.

These results allow us to draw the following conclusions:
• A 1% increase in the capital adequacy ratio leads to a decrease in the volume of non-performing loans by approximately 768.17 billion UZS.
• A 1 billion UZS increase in the volume of term deposits results in an increase in non-performing loans by around 65.5 million UZS.
• A 1% increase in the instant liquidity ratio raises the volume of non-performing loans by approximately 50.15 billion UZS.
This implies that while stronger capital adequacy has a stabilizing effect by reducing credit risk, increases in term deposits and higher liquidity levels are associated with rising NPL volumes during the observed period.
The statistical robustness of the ARMAX model is supported by several diagnostic results:
— Improved log-likelihood: The log-likelihood increased to –510.6, compared to –557 in the static model, indicating a better overall fit.
— Akaike Information Criterion (AIC): The AIC declined to 1035, which is lower than the lag-free model's value (~1123), confirming superior model specification.
— Model stability: The autoregressive root (AR = 1.149 > 1) lies outside the unit circle, demonstrating stationarity of the model.
— MA(1) term exclusion: The MA(1) coefficient was not statistically significant ($p > 0.25$) and was therefore removed, simplifying the model without compromising explanatory power.
Taken together, these diagnostics show that the dynamic ARMAX specification provides a more robust and statistically reliable framework for analyzing NPL dynamics and their determinants compared to the static regression model.
Moreover, the ARX(1) component of the model successfully captures the temporal dependence of the series. The inclusion of the lagged dependent variable Yt−1Y_{t-1}Yt−1 effectively eliminated residual autocorrelation, as confirmed by the Durbin–Watson test. This confirms the model's suitability for further analytical applications and short-term forecasting of NPL trends.
Subsequently, the study evaluates alternative ARIMA models using Stata to further refine the forecasting process. Three specifications were constructed: ARIMA(0,1,0), ARIMA(1,1,0), and ARIMA(0,1,1). A comparative analysis of these models is presented below, with detailed computations provided in the appendix.

Table 6 Comparative Analysis of the Models [6]:

Модель	**AIC (≈ 2k – 2LL)**	**Log-likelihood**	AR/MA Value	**Conclusion**
ARIMA(0,1,0)	**1014.14**	–506.072	—	Drift (constant): Statistically significant
ARIMA(1,1,0)	**1013.34**	–505.672	**AR:** Not statistically significant	AR(1): Redundant / not necessary
ARIMA(0,1,1)	**1013.41**	–505.705	**MA:** Not statistically significant	MA(1): Redundant / not necessary

Note: AIC ≈ –2 × LogL + 2k
By comparing the estimated models, the following conclusions can be drawn:

[6] Calculated using STATA software.

- In all three models, the Akaike Information Criterion (AIC) differences are very small (< 1), indicating that the models are equivalent in terms of fit quality.
- Both AR(1) and MA(1) terms are not statistically significant ($p > 0.3$).
- Only in ARIMA(0,1,0) is the constant (drift) statistically significant at the 5% level.

drift=300,27;   p=0,044.

4.4 ARIMA Model for Forecasting

Based on the calculations above, we constructed the simple ARIMA(0,1,0) model (Model 3):

$$Y_t = Y_{t-1} + 300{,}27 + \varepsilon_t$$

The results of the Ljung–Box test confirm that the residuals of the model are free from autocorrelation: Q=18.13Q = 18.13Q=18.13, p=0.1118p = 0.1118p=0.1118. Therefore, the model is adequate.

This implies that the ARIMA(0,1,0) model can be confidently used for future baseline forecasting based on the time series data.

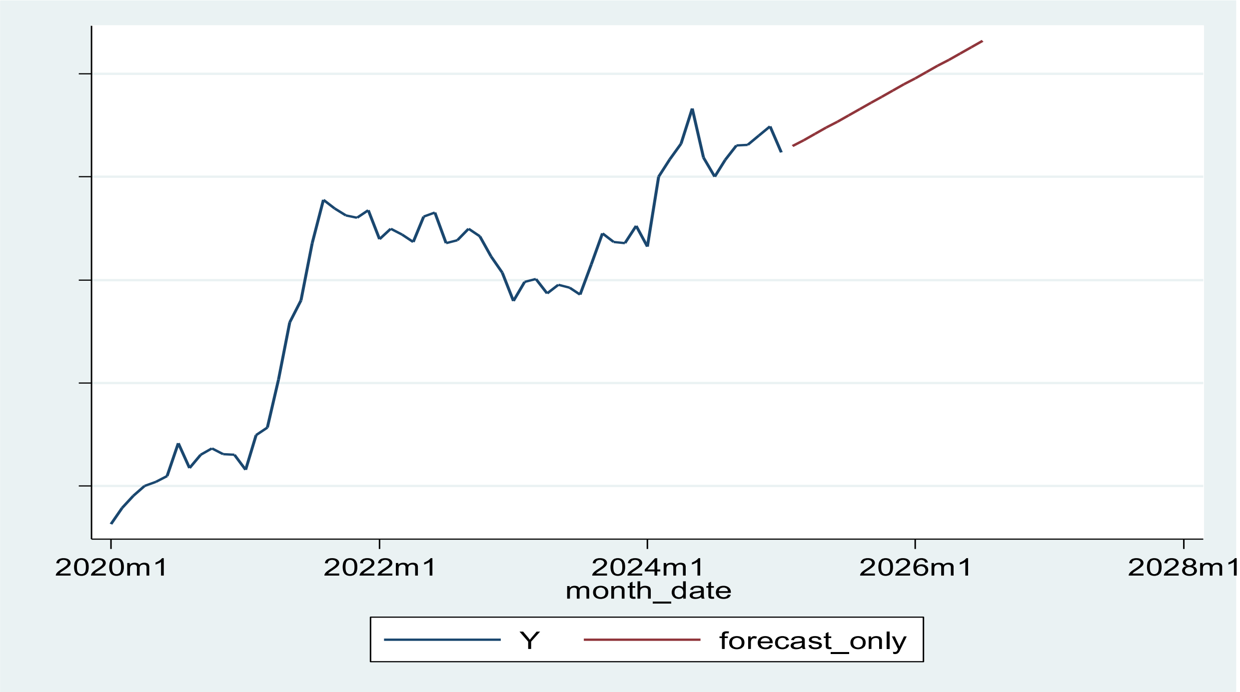

Figure 1. One-Year Forecast of Non-Performing Loans Based on the ARIMA(0,1,0) Model [7]

Based on the forecast generated by the ARIMA(0,1,0) model, it can be observed that the volume of non-performing loans is expected to increase steadily by approximately 300.27 units per month. Maintaining a high level of capital adequacy (X_1) plays a critical role in mitigating the risk of rising NPLs. In contrast, expansion of the deposit base (X_2) may contribute to the accumulation of non-performing assets if credit quality is not subject to strict monitoring and control.

Although a high liquidity ratio (X_5) generally indicates a stable banking system, it also requires prudent and balanced management. Relying on aggressive lending strategies solely on the basis of high

[7] Calculated using STATA software.

liquidity can increase credit exposure and heighten systemic risk. Overall, the ARIMA(0,1,0) forecast underscores the importance of robust capital management, prudent deposit expansion, and carefully balanced liquidity-driven lending strategies as key measures to contain the upward trajectory of NPLs.
The analysis was based on 61 monthly observations from January 2020 to January 2025. Initially, a correlation analysis was conducted to identify statistically significant relationships among variables. A linear regression model was then estimated, with the volume of non-performing loans (Y) as the dependent variable and capital adequacy ratio (X_1), volume of term deposits (X_2), and instant liquidity ratio (X_5) as explanatory variables. Although the coefficients were statistically significant, the model did not pass the autocorrelation diagnostic tests, necessitating the use of a dynamic modeling approach. To address this issue, the lagged dependent variable Yt−1Y_{t-1}Yt−1 was introduced, and an ARIMA (0,1,0) model was developed. This specification proved to be statistically reliable, capturing the underlying trend in the dependent variable, with NPL volumes rising at a stable monthly rate of approximately 300.27 units.
Subsequently, an ARMAX model was estimated to incorporate both exogenous factors and lagged dynamics. This model successfully passed diagnostic and stability tests, confirming its suitability for robust analysis and short-term forecasting. The final equation is expressed as:

$$\mathbf{Y_t = 17\,875{,}7 + 0{,}8703 \cdot Y_{t-1} + 0{,}1528 \cdot \varepsilon_{t-1} - 768{,}17 \cdot X1_t + 0{,}0655 \cdot X2_t + 50{,}15 \cdot X5_t + \varepsilon_t}$$

This model highlights the key drivers of the observed upward trend in non-performing loans:
— A 1% increase in capital adequacy reduces NPLs by approximately 768.17 billion UZS.
— A 1 billion UZS increase in term deposits increases NPLs by approximately 65.5 million UZS.
— A 1% increase in the instant liquidity ratio raises NPLs by around 50.15 billion UZS.

5. Conclusion

The results of this study provide strong empirical evidence that capital adequacy, term deposit volumes, and liquidity levels play a significant role in shaping the dynamics of non-performing loans in the banking sector. While higher capital adequacy contributes to a reduction in credit risk, increased deposit volumes and excessive liquidity may, under certain conditions, lead to a rise in NPL levels. These findings underscore the importance of proactive and balanced risk management strategies.
To address these challenges and strengthen financial stability, several policy measures are recommended. **First**, banks should strengthen oversight and control over the use of term deposits to prevent a deterioration in credit quality. **Second**, maintaining and supporting adequate capital buffers is crucial to enhancing the resilience and stability of the banking sector. **Finally**, the development and implementation of sound regulatory measures for balanced liquidity management and effective credit risk control will help ensure the sustainable and secure functioning of the financial system.
These measures, when implemented in an integrated manner, can significantly mitigate credit risk, improve the quality of credit services, and contribute to long-term banking sector stability in Uzbekistan.

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