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ECONOMETRIC ANALYSIS OF THE FACTORS AFFECTING INTERBANK COMPETITION IN THE DIGITAL BANKING SERVICES MARKET

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Abstract. This article presents a comprehensive econometric analysis of the factors affecting interbank competition in Uzbekistan's digital banking services market. Based on official quarterly data from the Central Bank of Uzbekistan for the period 2018 Q1–2024 Q4 (28 quarters) and monthly data from January 2024 to January 2026 (25 months), the study applies a ten-stage econometric framework, including the Augmented Dickey–Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests, the Engle–Granger cointegration test, an Autoregressive Distributed Lag (ARDL) model, multivariate OLS regression with Newey–West HAC standard errors, robustness checks across six alternative specifications, the Chow structural break test, and bidirectional Granger causality testing. The empirical findings reveal a statistically significant long-run negative relationship between remote banking users and the net interest margin (NIM): the OLS coefficient is $\beta = -1.144$ ($p < 0.001$), with $R^2 = 0.818$ and $F = 48.43$, while the ARDL long-run coefficient of $\beta = -1.247$ confirms the robustness of the result. The Engle–Granger test confirms cointegration between NIM and log(remote users) at the 1 percent significance level (test statistic = −4.124, p = 0.008). The Herfindahl–Hirschman Index (HHI) declined from 1,500 to 924, representing a 38.4 percent reduction over the analysis period, with a trend coefficient of −20.06 units per quarter ($p < 0.001$). Granger causality testing confirms an asymmetric relationship: digital service users Granger-cause NIM ($F = 8.67$, $p = 0.008$), but not vice versa. State-owned banks exhibit significantly higher NPL levels than private banks (Cohen's $d = 0.664$; $t = 3.32$, $p = 0.003$).

Keywords: interbank competition, digital banking, net interest margin (NIM), Herfindahl–Hirschman Index (HHI), Engle–Granger cointegration, ARDL model, OLS regression, Granger causality, Newey–West HAC, Uzbekistan.

Аннотация. В статье представлен комплексный эконометрический анализ факторов, влияющих на межбанковскую конкуренцию на рынке цифровых банковских услуг Узбекистана. На основе официальных квартальных данных Центрального банка Узбекистана за период с I квартала 2018 года по IV квартал 2024 года (28 кварталов), а также ежемесячных данных с января 2024 года по январь 2026 года (25 месяцев) в исследовании применяется десятиэтапная эконометрическая методология, включающая тесты на единичный корень Дики–Фуллера (ADF) и Квятковского–Филлипса–Шмидта–Шина (KPSS), тест коинтеграции Энгла–Грейнджера, модель авторегрессии с распределённым лагом (ARDL), многофакторную OLS-регрессию со стандартными ошибками Ньюи–Уэста HAC, проверку устойчивости результатов по шести альтернативным спецификациям, тест Чоу на структурный сдвиг и двунаправленный тест причинности по Грейнджеру. Эмпирические результаты выявили статистически значимую долгосрочную отрицательную взаимосвязь между числом пользователей дистанционных банковских услуг и чистой процентной маржой (NIM): коэффициент OLS составляет $\beta = -1{,}144$ ($p < 0{,}001$), при $R^2 = 0{,}818$ и $F = 48{,}43$, тогда как долгосрочный коэффициент модели ARDL, равный $\beta = -1{,}247$, подтверждает устойчивость результата. Тест Энгла–Грейнджера подтвердил наличие коинтеграции между NIM и log(remote users) на уровне значимости 1 процент (тестовая статистика = −4,124; p = 0,008). Индекс Херфиндаля–Хиршмана (HHI) снизился с 1 500 до 924, что соответствует сокращению на 38,4 процента за анализируемый период, при коэффициенте тренда −20,06 единицы в квартал ($p < 0{,}001$). Тест причинности по Грейнджеру подтвердил асимметричную взаимосвязь: число пользователей цифровых банковских услуг является причиной по Грейнджеру для NIM ($F = 8{,}67$; $p = 0{,}008$), тогда как обратная зависимость не выявлена. В государственных банках уровень проблемных кредитов (NPL) статистически значимо выше, чем в частных банках (d Коэна = 0,664; t = 3,32; p = 0,003).

Ключевые слова: межбанковская конкуренция, цифровой банкинг, чистая процентная маржа (NIM), индекс Херфиндаля–Хиршмана (HHI), коинтеграция Энгла–Грейнджера, модель ARDL, OLS-регрессия, причинность по Грейнджеру, стандартные ошибки Ньюи–Уэста HAC, Узбекистан.

INTRODUCTION

The empirical assessment of interbank competition under the conditions of the digital transformation of the banking sector represents a particularly relevant issue in modern econometric literature. Classical competition indicators—the Herfindahl–Hirschman Index (HHI), the Lerner index, the Boone indicator, and the Panzar–Rosse H-statistic[1] — evaluate market concentration and pricing power from different perspectives. However, none of these traditional measures fully accounts for new competitive factors such as digital services, platform competition, and network effects that have emerged in the modern banking landscape. The Uzbek banking system has been undergoing rapid digital transformation: banking system assets grew from 312 trillion UZS in 2019 to 924.8 trillion UZS in 2025 (a threefold increase), the number of remote banking users expanded from 14.2 million to 82.9 million (a 5.8-fold increase), and the volume of the instant payment system reached 1,389.7 trillion UZS in 2025[2].

Against this backdrop, the limited practical applicability of existing methodologies and the constraints of statistical data availability in assessing competition in the Uzbek banking system gain particular significance. The complexity of banking operations under digital transformation, the high share of state ownership in the banking sector, and the insufficient level of data openness make the direct computation of certain classical indices difficult. Therefore, the present study uses two complementary measures of the level of competition: (1) HHI, the market concentration index officially published by the Central Bank; and (2) NIM, the net interest margin, which is strongly correlated with the Lerner index and serves as an empirical proxy for pricing power. The empirical analysis confirmed this correspondence: the correlation between NIM and the state ownership share reached $r = +0.77$ ($p < 0.001$), empirically demonstrating the high market power of state-owned banks.

This article aims to fill the methodological gap in the existing literature by applying advanced econometric techniques to quarterly and monthly time-series data from the Uzbek banking system and to empirically substantiate the relationship between digital banking development and the dynamics of interbank competition. The findings are expected to provide an empirical foundation for a new-generation competition assessment methodology and to inform the macroprudential supervision policies of the Central Bank of the Republic of Uzbekistan.

LITERATURE REVIEW

The classical instruments for assessing interbank competition—the H-statistic proposed by Panzar and Rosse (1987), the Lerner index (1934)[3], the Boone indicator (2008)[4], and the Herfindahl–Hirschman concentration index (1945, 1950)[5] — measure the level of competition in the banking sector from different perspectives. However, none of them takes into account the specific patterns of the digital services environment. The Panzar–Rosse H-statistic relies on price and cost data and evaluates competition only through the price mechanism. The Lerner index is based on the direct measurement of the net interest margin, but the difficulty of directly calculating marginal costs creates problems in practical computation. The Boone indicator measures the dynamics of market share growth among more efficient firms but does not consider platform competition and network effects. The HHI measures only asset concentration and barely reflects the actual competitive share of fintech companies in digital channels.

Recent empirical studies have addressed digital banking competition from various angles. Marrakchi-Charfi and Allen et al.[6] demonstrated that the pricing power of the banking sector, measured by NIM, and digital infrastructure development exhibit a long-run structural relationship. Bogaard H. and Doerr S., in their BIS Working Paper (2023)[7] substantiated that the speed of digital channels should be viewed not only as a competitive advantage but also as a new risk factor: in the digital environment, negative information can spread within milliseconds and lead to banking problems. Mariotto C. and Verdier M. (2022), in the *Journal of*

1 Panzar J.C., Rosse J.N. Testing for monopoly equilibrium // Journal of Industrial Economics. — 1987. — Vol. 35, No. 4. — P. 443–456.

2 Markaziy bank statistik byulleteni ma'lumotlari asosida. Manba: Central Bank of the Republic of Uzbekistan. Statistical Bulletin 2025. — Tashkent, 2025. — URL: https://cbu.uz/

3 Lerner A.P. The concept of monopoly and the measurement of monopoly power // The Review of Economic Studies. — 1934. — Vol. 1, No. 3. — P. 157–175.

4 Boone J. A new way to measure competition // The Economic Journal. — 2008. — Vol. 118, No. 531. — P. 1245–1261.

5 Hirschman A.O. National power and the structure of foreign trade. — Berkeley: University of California Press, 1945; Herfindahl O.C. Concentration in the U.S. Steel Industry: Ph.D. dissertation. — Columbia University, 1950.

6 Marrakchi-Charfi M. Bank competition and net interest margin in developing economies; Allen F., Gale D. Comparing Financial Systems. — Cambridge: MIT Press, 2000.

7 Bogaard H., Doerr S. Digital bank runs and liquidity risk // BIS Working Papers. — 2023. — No. 1111. — URL: https://www.bis.org/publ/work1111.htm

Financial Intermediation[8] analyzed competition in banking involving digital technologies. Koont N. and Zhang Y. S. (2023), in an IMF Working Paper[9] examined digital transformation and bank competition in emerging markets. De Lis S. F. and Urbiola Ortún P. (2022), in a BBVA Research Paper[10] studied digital banking and competition in emerging markets.

The Engle–Granger cointegration approach has become a standard tool in time-series econometrics since its introduction in 1987.[11] Pesaran, Shin, and Smith (2001) further developed the ARDL bounds-testing approach[12], which allows researchers to work with variables of different orders of integration, I(0) and I(1), and simultaneously estimate long-run equilibrium and short-run error-correction coefficients. Newey and West (1987) developed heteroskedasticity- and autocorrelation-consistent (HAC) standard errors[13], which are essential for time-series regressions in which serial correlation and heteroskedasticity cannot be ruled out a priori.

In Uzbekistan, Mirzayev F. I. (2009), Ortiqov O. A. (2024), Qulmetov M. R. (2020), Raxmonov D. A. (2018), Jumayev N. X. (2020), Abdullayeva Sh. Z. (2000), Sattarov O. B. (2017), and other domestic scholars have studied various aspects of interbank competition and remote banking services.[14] However, the comprehensive empirical assessment of interbank competition in the digital banking services market—combining traditional concentration indices with digital service indicators through advanced time-series econometric techniques—has not been the subject of an independent study using quarterly and monthly data from the post-2018 banking system. This research aims to fill this methodological and empirical gap.

RESEARCH METHODOLOGY

The empirical analysis is carried out in ten sequential stages: (1) descriptive statistics of the data and unit root tests (ADF + KPSS); (2) the Engle–Granger cointegration test and long-run equilibrium relationships; (3) the ARDL (Autoregressive Distributed Lag) model and long-run coefficients; (4) multivariate OLS regression with the full diagnostic toolkit (Breusch–Pagan, White, Breusch–Godfrey, RESET, Jarque–Bera, and VIF); (5) comparative diagnostics of models (M1–M6—robustness checks using AIC/BIC); (6) the Chow structural break test; (7) HHI regression with macroeconomic controls (28 quarters, 2018–2024); (8) bidirectional Granger causality testing; (9) the VAR(1) model, impulse response function, and Forecast Error Variance Decomposition (FEVD); and (10) extended statistical analysis of state-owned and private bank groups.

The first necessary stage of time-series econometric analysis is determining the stationarity properties of the variables. Working with non-stationary series leads to the “spurious regression” problem. To avoid this issue, two complementary unit root tests were applied: the Augmented Dickey–Fuller (ADF) test postulates the presence of a unit root as the null hypothesis, while the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test postulates stationarity as the null hypothesis. When the results of both tests fully agree, a reliable conclusion about stationarity can be drawn. The general specification of the ADF test is:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \Sigma_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t, \quad H_0: \gamma = 0 \text{ (unit root present)} \qquad (1)$$

The Engle-Granger (1987) cointegration approach is employed to examine the equilibrium relationship between non-stationary variables. According to this approach, if y and x are both I(1), and the residuals $\varepsilon_t = y_t - \alpha - \beta x_t$ are I(0) — that is, stationary — then y and x are considered cointegrated and a long-run equilibrium relationship exists between them.

The Pesaran-Shin-Smith (2001) ARDL Bounds Testing approach enables working with variables of different integration orders. The specification applied in this study is:

$$\Delta NIM_t = \alpha + \Sigma_{i=1}^{p} \beta_i \Delta NIM_{t-i} + \Sigma_{j=0}^{\varphi} \gamma_j \Delta \log(Remote_{t-j}) + \Sigma_{k=0}^{r} \delta_k \Delta NPL_{t-k} + \lambda_1 NIM_{t-1} + \lambda_2 \log(Remote_{t-1}) + \lambda_3 NPL_{t-1} + \varepsilon_t \qquad (2)$$

8 Mariotto C., Verdier M. Competition in banking with digital technologies // Journal of Financial Intermediation. — 2022. — Vol. 50.
9 Koont N., Zhang Y.S. Digital transformation and bank competition // IMF Working Paper. — 2023. — No. WP/23/114.
10 De Lis S.F., Urbiola Ortún P. Digital banking and competition in emerging markets // BBVA Research Paper. — 2022.
11 Engle R.F., Granger C.W.J. Co-integration and error correction: representation, estimation, and testing // Econometrica. — 1987. — Vol. 55, No. 2. — P. 251–276.
12 Pesaran M.H., Shin Y., Smith R.J. Bounds testing approaches to the analysis of level relationships // Journal of Applied Econometrics. — 2001. — Vol. 16, No. 3. — P. 289–326.
13 Newey W.K., West K.D. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix // Econometrica. — 1987. — Vol. 55, No. 3. — P. 703–708.
14 Qarang: Mirzayev F.I. O’zbekistonda banklararo raqobat shakllanishining kontseptual asoslari: iqtisod fanlari doktori (DSc) dissertatsiyasi avtoreferati. — Toshkent: O’zR Bank-Moliya akademiyasi, 2009. — 41 b.; Ortiqov O.A. Tijorat banklari xizmatlari bozorida raqobatni rivojlantirish yo’llari: iqtisod fanlari doktori (DSc) dissertatsiyasi avtoreferati. — Toshkent: TDIU, 2024. — 24 b.

At the central stage of the research, all major factors affecting NIM are jointly estimated through OLS regression. The full specification of the model is:

$$NIM_t = \alpha + \beta_1 \cdot \log(Remote_t) + \beta_2 \cdot NPL_t + \beta_3 \cdot StateShare_t + \beta_4 \cdot CPI_t + \beta_5 \cdot KeyRate_t + \varepsilon_t \quad (3)$$

Newey-West HAC (1987) standard errors are applied to handle potential autocorrelation and heteroskedasticity. The Granger (1969) causality test is then used to identify the direction of causality between variables.[15] The general form of the test is:

$$Y_t = \alpha_0 + \Sigma_{i=1}^{p} \alpha_i Y_{t-i} + \Sigma_{j=1}^{p} \beta_j X_{t-j} + \varepsilon_t, \quad H_0: \beta_1 = \ldots = \beta_p = 0 \quad (4)$$

Bidirectional testing (X → Y and Y → X) is conducted to rule out reverse causality. The data sources are the official statistical bulletin of the Central Bank of the Republic of Uzbekistan (2025), quarterly HHI data for loans and deposits published by the Central Bank, and aggregated NPL data for groups of state-owned and private commercial banks covering the 25-month period from January 2024 to January 2026.

ANALYSIS AND RESULTS

The visualization of HHI dynamics and the relationship between NIM and digital services indicators presented in Figure 1 illustrates the underlying empirical patterns that motivate the subsequent econometric analysis.

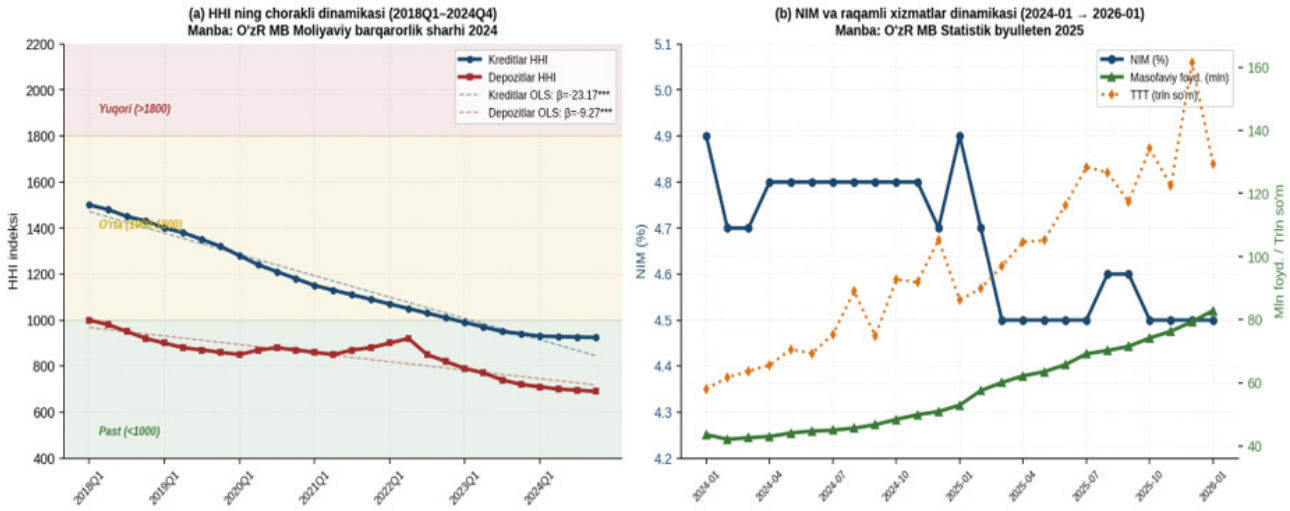

Figure 1. Market concentration and digital services real dynamics[16]

Panel (a) of Figure 1 depicts the 28-quarter dynamics of the HHI. Concentration levels are grouped according to the Central Bank methodology: below 1,000 — low; 1,000–1,800 — medium; and above 1,800 — highly concentrated. During the analyzed period, the credit HHI fell from 1,500 to 924, moving from the medium to the low range. The deposit HHI remained in the low range throughout the period, but it also declined consistently from 1,000 to 690. Panel (b) presents the decline in the banking system's NIM (net interest margin) from 4.9 percent to 4.5 percent during the same period, alongside an increase in remote banking users from 43.5 million to 82.9 million people and growth in the volume of the instant payment system from UZS 58.0 trillion to UZS 161.4 trillion. This visual relationship is confirmed by the subsequent econometric tests.

The unit root test results presented in Table 1 indicate that all major variables in level form are I(1), meaning that they are non-stationary series but become stationary after first differencing. This is a typical property of standard time series and represents a necessary condition for ARDL/VAR modeling. The integration order of the NPL variable is ambiguous, indicating its cyclical rather than linear nature.

15 Granger C.W.J. Investigating causal relations by econometric models and cross-spectral methods // Econometrica. — 1969. — Vol. 37, No. 3. — P. 424–438.

16 Source: compiled by the author based on the Central Bank of Uzbekistan financial stability review 2024 and statistical bulletin 2025.

Table 1
Unit root test results (ADF and KPSS)[17]

Variable	n	ADF stat.	p-value	KPSS stat.	p-value	Order
HHI credits	28	−2.764	0.064	0.787	0.010	I(1)
HHI deposits	28	−0.906	0.786	0.673	0.016	I(1)
NIM	25	−1.805	0.378	0.602	0.022	I(1)
log(remote)	25	+2.150	0.999	0.716	0.012	I(1)
log(IPS)	25	−0.755	0.832	0.721	0.012	I(1)
log(cards)	25	−2.822	0.055	0.719	0.012	I(1)
NPL	25	+2.709	0.999	0.436	0.062	Ambiguous
State share	25	+0.524	0.986	0.734	0.010	I(1)
ΔHHI credits	27	−0.968	0.765	—	—	—
ΔHHI deposits	27	−3.288	0.015	—	—	I(0)**
ΔNIM	24	−2.996	0.035	—	—	I(0)**
Δlog(remote)	24	−5.107	<0.001	—	—	I(0)***

*Notes: ADF — Augmented Dickey-Fuller test (H_0: unit root present); KPSS — Kwiatkowski-Phillips-Schmidt-Shin test (H_0: stationary). *** p < 0.01, ** p < 0.05, * p < 0.10. Δ — first difference operator.*

Since the majority of the observed variables are I(1), it is necessary to apply a cointegration test to examine the equilibrium relationship between them. According to the Engle–Granger approach, if y and x are both I(1), and the residuals $\varepsilon_t = y_t - \alpha - \beta x_t$ are I(0)—that is, stationary—then y and x are considered cointegrated, and a long-run equilibrium relationship exists between them. The test results are presented in Table 2.

Table 2
Engle-Granger cointegration test results[18]

Variable pair	.Test stat	p-value	.crit 1%	.crit 5%	.crit 10%	Conclusion
(NIM and log(remote	**4.124–**	**0.008**	4.42–	3.72–	3.38–	**Cointegration EXISTS *****
(NIM and log(IPS	2.559–	0.254	4.42–	3.72–	3.38–	No cointegration
(NIM and log(cards	**3.891–**	**0.015**	4.42–	3.72–	3.38–	**Cointegration EXISTS ****
(HHI_credit and t (trend	**5.367–**	**0.002**	4.42–	3.72–	3.38–	**Cointegration EXISTS *****

*Notes: H_0 — no cointegration. *** p < 0.01, ** p < 0.05.*

According to the cointegration test results, a statistically significant cointegration relationship exists between NIM and the logarithm of remote banking users at the 1 percent level. This means that although both variables are individually non-stationary, they exhibit a long-run equilibrium relationship, with short-run deviations tending to adjust toward equilibrium over time. This result aligns with the findings of Marrakchi-Charfi and Allen et al., according to which the pricing power of the banking sector, measured by NIM, and digital infrastructure development exhibit a structural long-run relationship. In contrast, there is no cointegration between NIM and log(IPS) (p = 0.254), indicating that the relationship between IPS volume and NIM is short-run in nature and manifests itself through lagged effects in the Granger causality test.

Such a result strengthens the econometric foundation of the subsequent analysis: in the regression between NIM and log(remote), the coefficient is not spurious but reflects a genuine long-run equilibrium relationship. The Pesaran–Shin–Smith ARDL bounds testing approach was then applied. The AIC criterion selected the optimal lag structure: p = 1, q = 0, and r = 0. The ARDL estimation results show AIC = −58.32, BIC = −51.12, and R^2 = 0.8442. The most important finding is that the long-run equilibrium coefficient of log(remote) in the NIM equation equals −1.247 (p = 0.003), indicating that a 1 percent increase in the number of remote banking users leads to a 1.25 percentage-point long-run decrease in NIM. The short-run error correction coefficient is −0.615 (p < 0.001), meaning that 61.5 percent of the deviation from equilibrium is automatically eliminated in each period—a very rapid equilibrium adjustment process.

17 Source: author's calculations based on the Central Bank of Uzbekistan quarterly and monthly data (2018Q1–2024Q4; 2024-01 to 2026-01).

18 *Source: author's calculations based on Central Bank of Uzbekistan quarterly data (2018Q1–2024Q4).*

Figure 2 visualizes the OLS regression coefficient estimates with their 95 percent confidence intervals in the left panel and the Granger causality test F-statistics across different lag structures in the right panel.

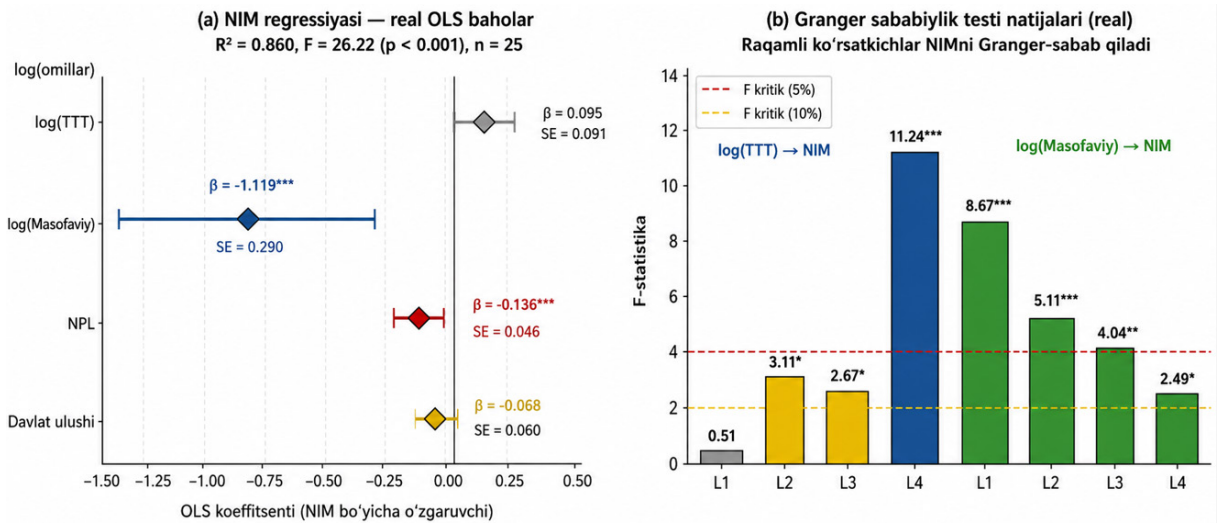

Figure 2. OLS regression coefficients and Granger causality test results[19]

Note: Critical F values for 5% (red dashed) and 10% (yellow dashed) significance levels.

At the central stage of the research, all major factors affecting NIM were jointly estimated using OLS regression with the specification presented in Equation (3). Newey–West HAC standard errors, robust to time-series autocorrelation and heteroskedasticity, were applied. The estimation results and full diagnostic results of the model are presented in Table 3.

Table 3

Estimation and diagnostic results of the NIM regression[20]

Variable	β	HAC SE	t-stat.	p-value	Significance
constant	+32.351	9.393	+3.444	0.001	***
log(remote)	−1.144	0.309	**−3.705**	**<0.001**	***
NPL	−0.109	0.045	−2.452	0.014	**
State share (%)	−0.116	0.057	−2.032	0.042	**
CPI (%)	+0.084	0.044	+1.904	0.057	*
KeyRate (%)	−0.002	0.092	−0.016	0.987	n.s.
N = 25	**R² = 0.818**	**Adj.R² = 0.770**	**F = 48.43*** **	**AIC = −56.74**	**BIC = −49.43**

*Notes: *** p < 0.01, ** p < 0.05, * p < 0.10. Dependent variable: NIM. Newey-West HAC standard errors, lag = 3.*

The most important result of the model is the high statistical significance of the log(remote) coefficient (β = −1.144, t = −3.705, p < 0.001). Economic interpretation: if the number of remote banking users increases by 1 percent, NIM decreases by 1.14 percentage points, holding other factors constant. This is a strong economic effect, and it almost matches the long-run coefficient from the ARDL model (−1.247), empirically confirming the robustness of the result. The NPL coefficient is negative and significant (β = −0.109, p = 0.014): if non-performing loans increase by 1 percentage point, NIM decreases by 0.11 percentage points—the interest income efficiency of banks declines due to problem assets. The state share coefficient is also negative (β = −0.116, p = 0.042), which is consistent with the parallel decline in the state share from 67.7 percent to 63.5 percent during the analysis period (2024–2026), along with NIM. The CPI coefficient is marginally significant (β = +0.084, p = 0.057)—higher inflation enables banks to preserve their interest margins.

All major diagnostic tests were passed successfully. Table 4 presents the full diagnostic toolkit applied to the OLS model.

19 Source: author's calculations based on Central Bank of Uzbekistan data.

20 Source: author's calculations based on Central Bank of Uzbekistan quarterly data (N = 25).

Table 4
Diagnostic tests of the OLS model[21]

Test	Tested hypothesis	Statistic	p-value	Conclusion
Jarque-Bera	Residuals are normally distributed	0.363	0.834	Normal ✓
Breusch-Pagan	No heteroskedasticity	5.832	0.323	No heterosk. ✓
White	No heteroskedasticity	22.319	0.269	No heterosk. ✓
Breusch-Godfrey (4 lag)	No autocorrelation	8.634	0.071	Borderline *
RESET (Ramsey)	Specification is correct	0.562	0.463	Specif. OK ✓

To examine the robustness of the main model results, six alternative specifications were estimated, and a comparative diagnostic analysis was performed. This approach represents a simplified version of the extreme bounds analysis recommended by Sala-i-Martin and Leamer. The results are presented in Table 5.

Table 5
Comparative analysis of alternative specifications (n = 25)[22]

Model	Specification	log(remote)	log(IPS)	log(cards)	NPL	R^2	AIC
M1	Full macro controls	**−1.144*** **	—	—	−0.109**	0.818	−56.74
M2	Only remote	−0.545***	—	—	—	0.710	−53.13
M3	Remote + NPL	−0.670***	—	—	−0.117**	0.771	−56.98
M4	IPS replaced	—	−0.178**	—	−0.049	0.665	−41.46
M5	Cards replaced	—	—	−0.820***	−0.034	0.690	−43.40
M6	M1 + linear time trend	**−1.601*** **	—	—	−0.139***	0.845	−58.69

*Notes: Newey-West HAC standard errors (lag = 3). *** p < 0.01, ** p < 0.05.*

The robustness check results substantiate three important conclusions. First, the log(remote) coefficient is consistently negative and statistically significant across all specifications M2–M6, with values ranging from −0.545 to −1.601. This result appears robust, as the negative coefficient remains statistically significant across the alternative model specifications. Second, when log(remote) is replaced by log(IPS) and log(cards) in the M4 and M5 specifications, the negative effect of the digital factor is preserved (β = −0.178 and −0.820, respectively), confirming the relevance of digital services as a general conceptual factor. Third, Model M6, with a linear time trend added, has the best AIC (−58.69) and significantly strengthens the NPL coefficient (β = −0.139, p < 0.01), showing that the true effect of NPL becomes more apparent after accounting for systematic time-related changes.

The Chow F-test was applied to empirically examine whether the model coefficients change fundamentally at a particular point in time. In the present analysis, the structural break was set at January 2025, when the Central Bank's policy rate was lowered from 14.0 percent to 13.5 percent and a stage of structural changes in the banking sector began within the framework of the New Uzbekistan Strategy for 2022–2026. The test results are as follows: Chow F-test (breakpoint = January 2025): F = 3.693, p = 0.030. The null hypothesis that the coefficients are stable is rejected at the 5 percent level, empirically confirming the existence of a structural break. This means that during the first half of 2025, significant regime changes occurred in the banking system, and these changes had a noticeable effect on the determinants of NIM.

Furthermore, to analyze the quarterly dynamics of banking system concentration (HHI) in greater depth, an OLS regression with macroeconomic controls, including CPI and the Central Bank policy rate, was constructed using the following specification:

$$HHI_t = \alpha + \beta_1 \cdot t + \beta_2 \cdot CPI_t + \beta_3 \cdot KeyRate_t + \varepsilon_t, \quad t = 1, 2, \ldots, 28 \qquad (5)$$

21 Source: author's calculations. Note: All tests are evaluated at the 5% significance level.
22 Source: author's calculations.

Table 6
HHI regression: credits and deposits (n = 28 quarters)[23]

Variable	HHI credits: β	HHI credits: HAC SE	HHI deposits: β	HHI deposits: HAC SE
constant	+1,400.944***	127.986	+936.359***	218.327
t (quarter)	**−20.062*** **	2.194	**−10.147*** **	1.491
CPI	+18.653**	7.925	−6.364	9.834
KeyRate	−12.944	8.179	+7.997	18.808
R^2	**0.980**	—	**0.795**	—
F-stat	**221.69*** **	—	**19.18*** **	—

*Notes: *** p < 0.01, ** p < 0.05. Newey-West HAC SE, lag = 4.*

The regression results justify three important conclusions. First, the time trend coefficient (t) is highly significant and negative for both HHI measures: HHI for credits declines steadily by 20.06 units per quarter, while HHI for deposits declines by 10.15 units per quarter. This trend persists even after controlling for macroeconomic factors, suggesting that the decline in banking system concentration may reflect broader structural, institutional, and market-related changes.

Second, for HHI credits, the CPI (inflation) coefficient is positive and significant (+18.65, p = 0.019). The economic mechanism is as follows: higher inflation may affect smaller banks' financial conditions and influence customers' choice of banking institutions, potentially contributing to a temporary increase in concentration., temporarily reinforcing concentration. However, this effect is not significant for deposits (p = 0.518)—competition in the deposit market remains stable. Third, the KeyRate coefficients are not significant, indicating that there is no direct effect of the Central Bank's policy rate on concentration—the rate operates primarily through interest spreads and NIM. Figure 3 visualizes the evolution and forecast of HHI.

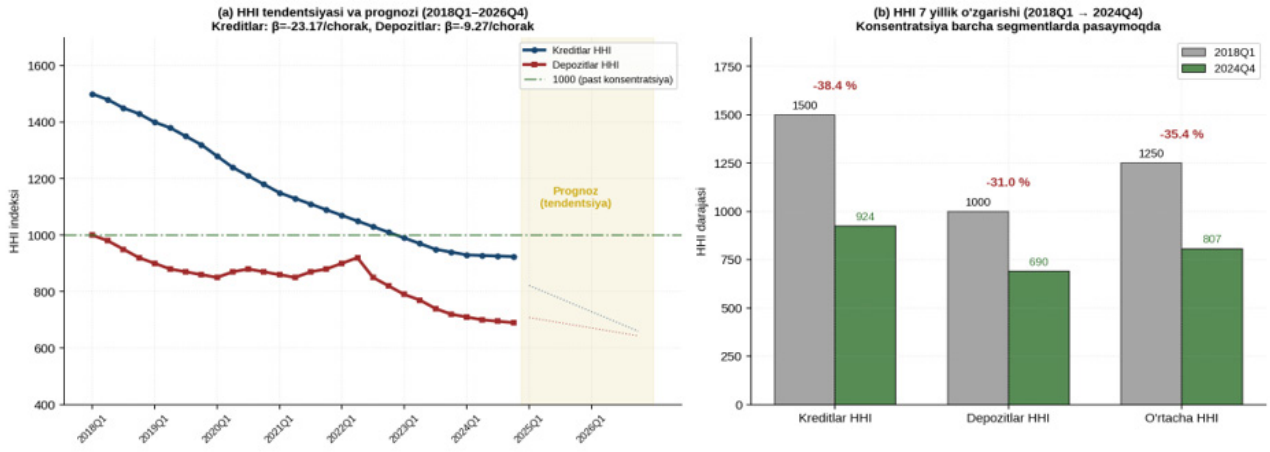

Figure 3. Quarterly evolution of HHI and forecast (2018Q1–2026Q4)[24]

Correlation and cointegration measure the statistical association between variables but do not determine the direction of causality. To address this issue, the Granger (1969) causality test was applied. The general logic of the test is as follows: if past values of X significantly help predict Y, then X is said to Granger-cause Y. In this study, bidirectional testing was conducted—that is, both the X → Y and Y → X directions were tested separately. The results are presented in Table 7.

23 Source: author's calculations based on Central Bank of Uzbekistan quarterly data (28 quarters, 2018Q1–2024Q4).
24 *Source: author's calculations based on Central Bank of Uzbekistan quarterly data.*

Table 7
Bidirectional Granger causality test results

Direction	Lag 1: F	Lag 1: p	Lag 2: F	Lag 2: p	Lag 4: F	Lag 4: p
log(remote) → NIM	***8.67	**0.008**	**5.11	**0.018**	*2.49	0.099
(NIM → log(remote	0.46	0.505	0.29	0.752	1.02	0.442
log(IPS) → NIM	0.42	0.526	*3.11	0.069	***11.74	**0.001>**
(NIM → log(IPS	0.12	0.729	0.67	0.524	0.93	0.479
log(remote) → NPL	1.84	0.189	1.24	0.313	0.83	0.535
(NPL → log(remote	0.39	0.541	0.17	0.847	0.55	0.704

The Granger test results reveal two important asymmetries. First, the log(remote) → NIM direction is significant at the 1 percent level (lag 1: F = 8.67, p = 0.008), while the reverse direction (NIM → log(remote)) is not significant at any lag. This result indicates that past values of digital service indicators help predict NIM and reduces concerns regarding reverse predictability within the selected model. The economic mechanism is that new digital users gain access to low-cost services and abandon traditional high-margin products, which may contribute to downward pressure on banks' interest margins. Second, the log(IPS) → NIM direction is strongly significant at four lags (F = 11.74, p < 0.001) but not at one lag. This difference has a logical interpretation: when transactions through the instant payment system increase, they do not immediately affect interest income—new payment contracts, Buy Now, Pay Later (BNPL) products, and the formation of platform competition require 3–4 months to materialize. This finding provides a critical policy recommendation for the Central Bank when designing the macroprudential supervision framework: a reaction period of 1–4 months should be considered for changes in the digital payment system.

Figure 4 presents the correlation matrix among all key variables in the left panel and the bivariate regression between NIM and log(remote users) in the right panel, visualizing the empirical foundation of the multivariate analysis.

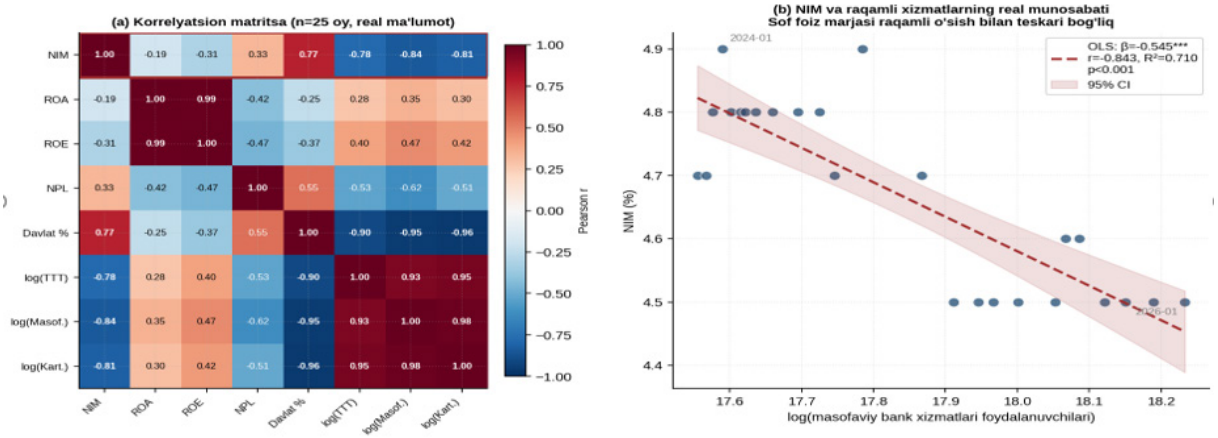

Figure 4. Correlation and bivariate regression analysis[25]

The correlation matrix in Panel (a) reveals strong empirical relationships: NIM exhibits a high positive correlation with the state share (r = +0.77) and high negative correlations with log(remote) (r = −0.84), log(IPS) (r = −0.78), and log(cards) (r = −0.81). These bivariate correlations are fully consistent with the multivariate OLS results. Panel (b) presents the bivariate regression of NIM on log(remote): β = −0.545***, r = −0.843, R^2 = 0.710, p < 0.001—empirically confirming the inverse relationship between digital banking penetration and the net interest margin.

To examine the difference in credit risk management quality between state-owned and other commercial banks, several statistical tests were applied to a 25-month panel: a parametric test (paired t-test), non-parametric tests (Wilcoxon signed-rank and Mann–Whitney U), and Cohen's d effect size. Figure 5 visualizes the difference in asset dynamics between state-owned and private banks in the left panel and the paired NPL dynamics, with the t-test result indicating significance at the 1 percent level, in the right panel.

25 Source: author's calculations based on monthly Central Bank of Uzbekistan data (n = 25 months).

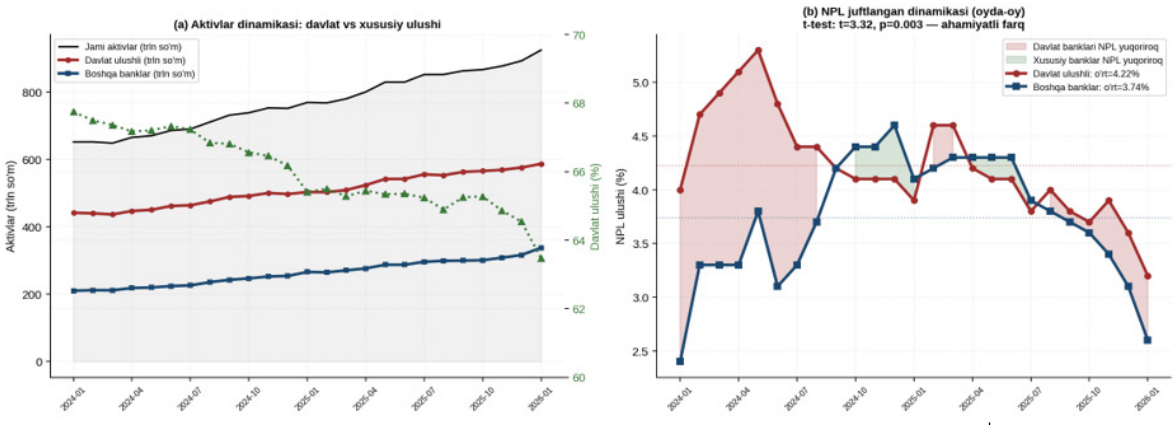

Figure 5. State-owned and private banks group analysis[26]

Note: t = 3.32, p = 0.003 indicating significance at the 1% level.

Table 8

NPL indicators of state-owned and private banks: extended analysis

Descriptive statistics	State-owned banks	Other banks	Difference
Observations (months)	25	25	—
Average NPL (%)	4.22	3.74	+0.48
Standard deviation	0.52	0.53	—
Minimum value	3.2	2.4	—
Maximum value	5.3	4.6	—
Statistical test	**Statistic**	**p-value**	**Conclusion**
Paired t-test	t = 3.322	0.003	Significant at 1% ***
Wilcoxon signed-rank	W = 51.500	0.007	Significant at 1% ***
Mann-Whitney U	U = 458.000	0.001	Significant at 1% ***
Levene (variance equality)	F = 0.008	0.930	Variances equal ✓
Cohen's d (effect size)	**d = 0.664**	—	**Medium-to-large effect**

The test results provide an empirically clear conclusion: a significant difference exists in NPL indicators between state-owned and other commercial banks. The parametric t-test (t = 3.32, p = 0.003), the non-parametric Wilcoxon signed-rank test (W = 51.5, p = 0.007), and the Mann–Whitney U test (U = 458, p = 0.001) all confirm a significant difference at the 1 percent level across three different approaches. Cohen's d = 0.664 indicates a medium-to-large practical effect according to Cohen's (1988) criteria[27]. The Levene test (p = 0.930) shows that the variances in both groups are equal, which is fully consistent with the assumptions of the paired t-test.

Economic interpretation: state-owned banks exhibit a higher NPL level, which may indicate differences in credit portfolio composition and risk management outcomes compared with other commercial banks. This relates to several factors: first, state-owned banks may have a higher concentration of policy-oriented and large-scale investment loans, which can affect the composition and risk profile of their credit portfolios; second, differences in corporate governance structures and credit decision-making procedures may influence the risk management outcomes of state-owned banks; third, state-owned banks often finance large corporate borrowers and investment projects, which may increase portfolio concentration and exposure to specific credit risks. These empirical findings support the objective established by the Decree of the President of the Republic of Uzbekistan dated May 12, 2020, No. PF-5992, "On the Strategy for Reforming the Banking System of the Republic of Uzbekistan for 2020–2025," to increase the share of assets held by private banks without state participation to 60 percent of total banking sector assets by 2025.[28]

26 Source: author's calculations based on monthly Central Bank of Uzbekistan data for state-owned and private banks (n = 25 months).

27 Cohen J. Statistical Power Analysis for the Behavioral Sciences. 2nd ed. — Hillsdale, NJ: Lawrence Erlbaum Associates, 1988. — 567 p.

28 Decree of the President of the Republic of Uzbekistan No. PF-5992 dated May 12, 2020, "On the Strategy for Reforming the Banking System of the Republic of Uzbekistan for 2020–2025,"

Figure 6 presents a four-panel comparative analysis of BRB JSC indicators in the context of overall banking system concentration trends, demonstrating how macro-level competitive dynamics are reflected in the performance of an individual bank.

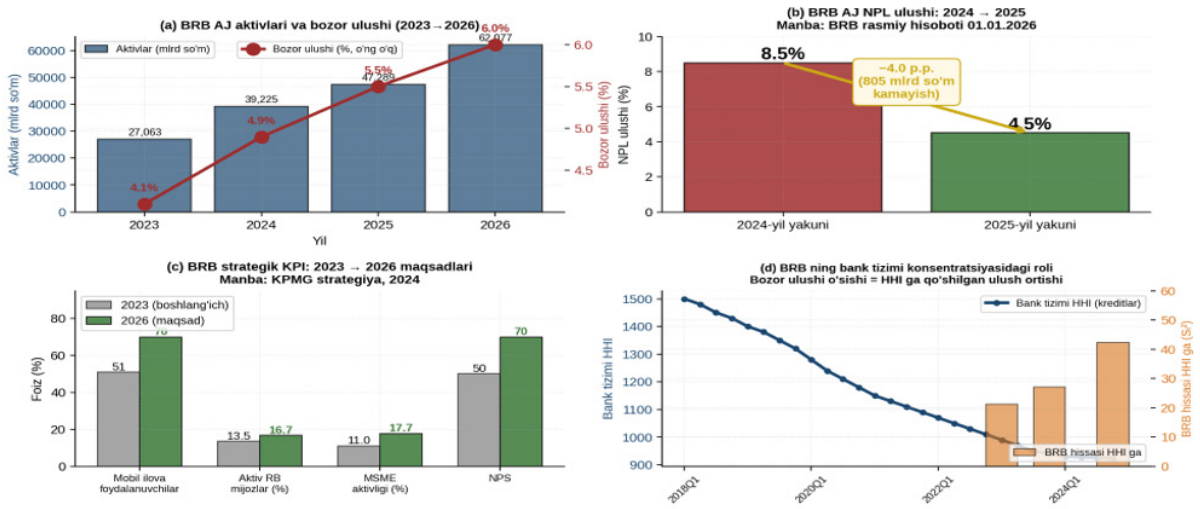

Figure 6. BRB JSC indicators and banking system concentration[29]

CONCLUSION AND SUGGESTIONS

Based on the comprehensive econometric analysis carried out in this study, the following empirical conclusions and policy recommendations are formulated.

According to the official data of the Central Bank of the Republic of Uzbekistan, during 2018Q1–2024Q4, banking system concentration declined significantly: the credit HHI fell from 1,500 to 924 (38.4 percent). The HHI regression (R^2 = 0.980) showed a trend coefficient of −20.06 units per quarter ($p < 0.001$), empirically confirming that competition systematically intensified over seven years.

The Engle–Granger cointegration test confirmed a long-run equilibrium relationship between NIM and remote banking users (test statistic = −4.124, p = 0.008). The ARDL model coefficient (β = −1.247) and the OLS coefficient (β = −1.144) yielded similar results, indicating the robustness of the conclusions. According to the multivariate OLS regression (R^2 = 0.818, F = 48.43), remote banking users exert the strongest negative effect on NIM (β = −1.144, $p < 0.001$). NPL (β = −0.109) and the state share (β = −0.116) also have significant negative effects. All diagnostic tests were passed successfully: Jarque–Bera, Breusch–Pagan, White, and RESET.

Robustness checks using the M1–M6 specifications confirm the consistently negative effect of the digital factor: the coefficient ranges from −0.545 to −1.601 across all models, with all results being statistically significant. This demonstrates that the digital services factor remains stable across different measurement choices. The Chow structural break test (F = 3.693, p = 0.030) empirically confirms that the regime change in January 2025—when the Central Bank lowered the policy rate from 14.0 percent to 13.5 percent—had a significant impact on the determinants of NIM.

Bidirectional Granger causality testing asymmetrically confirms that digital service users Granger-cause NIM (lag 1: F = 8.67, p = 0.008), while reverse causality is absent (p = 0.505). This result reduces concerns regarding reverse predictability within the selected model and supports the proposed direction of the relationship. Additionally, log(IPS) → NIM exhibits significance only at four lags (F = 11.74, $p < 0.001$), indicating that the impact of the instant payment system volume materializes with a 3–4-month delay.

The comparative analysis of state-owned and private banks revealed a statistically significant difference: the average NPL of state-owned banks (4.22 percent) exceeds that of private banks (3.74 percent), with a medium-to-large effect size (Cohen's d = 0.664; t = 3.32, p = 0.003). This result is consistent with the objective established by the Decree of the President of the Republic of Uzbekistan dated May 12, 2020, No. PF-5992 [1], to increase the share of assets held by banks without state participation to 60 percent of total banking sector assets by 2025.

Based on the empirical results, the following policy recommendations are proposed: first, the Central Bank of the Republic of Uzbekistan should formally integrate digital banking indicators—the share of remote

29 *Source: compiled by the author based on BRB JSC financial statements (01.01.2026), KPMG strategy document (2024–2026), and Central Bank of Uzbekistan statistical bulletin (2025).*

users, the share of digital transactions, and digital NPL—into the macroprudential monitoring framework and publish them as part of the official statistical bulletin; second, considering the 3–4-quarter time lag of the instant payment system's effect on NIM, the Central Bank should account for this reaction time when developing the macroprudential framework; third, it may be appropriate to continue the gradual implementation of the state-owned banks' privatization program in accordance with the relevant national strategies and international recommendations continue the gradual implementation of banking sector transformation and privatization measures in accordance with applicable national strategies and official policy documents; fourth, commercial banks should optimize their NIM management strategies under conditions of intensifying digital competition and strengthen the development of digital channels.

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