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Article

Digital Factors of Commercial Bank Liquidity: An SVAR Analysis (In Case of Uzbekistan)

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Abstract: This study evaluates the possibilities of digital analysis and econometric modelling for ensuring the liquidity of commercial banks in Uzbekistan. Using monthly data of the Central Bank of the Republic of Uzbekistan for January 2017 – December 2025 (108 observations), four recursively identified Structural Vector Autoregression (SVAR) models are estimated, in which the dependent liquidity indicators are the ratio of highly liquid assets to total assets (HQLA/TA), the liquidity coverage ratio (LCR), the net stable funding ratio (NSFR) and the instant liquidity ratio (ILR), while inflation, real broad money, the money market rate, remote banking users and real POS turnover act as macroeconomic and digital factors. Stationarity, Johansen cointegration, lag selection and Granger causality tests are followed by impulse response analysis, forecast error variance decomposition, a stress test and a signal-based early warning system. Real money supply is the main external driver of liquidity, explaining 7–19% of its variability. The rapid expansion of remote banking has a negative cumulative effect on liquidity in all four models, Granger-causes the LCR at the 10% level and explains 5.1% of LCR variability, whereas POS turnover has no significant effect. Even under the worst historical 12-month scenario all ratios remain above the regulatory minimums, but the LCR buffer shrinks to only 3.2 percentage points.

Keywords: bank liquidity; liquidity coverage ratio (LCR); net stable funding ratio (NSFR); Structural Vector Autoregression (SVAR); remote banking; impulse response function; variance decomposition; stress test; early warning system; Uzbekistan.

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1. Introduction

The rapid digitalisation of banking systems worldwide – the migration of financial services to remote channels, the expansion of instant payment systems and the growing ability of customers to use banking services in real time – is turning the problem of ensuring commercial bank liquidity into one of the most pressing economic issues. Digital channels make funds more mobile: customers can close a deposit in a mobile application within seconds and move it to another bank. The bank failures in the United States in 2023 demonstrated that deposits can leave through digital channels within hours, while the Basel III liquidity coverage ratio is calibrated on a 30-day stress horizon.

In Uzbekistan the banking sector has undergone a profound digital transformation. Between 2017 and 2025 the number of remote banking users increased from 2.8 million to 82.9 million in the monthly series used in this study, and real POS turnover grew particularly fast after 2021. At the same time, liquidity indicators improved: the LCR remained well above the regulatory requirement throughout the period, the NSFR rose steadily to 119.9%, and the instant liquidity ratio increased to 134.7% by the end of 2025.

Whether digitalisation strengthens or weakens bank liquidity, however, remains an open empirical question for the country.[1]

The current liquidity monitoring framework of the Central Bank is based on monthly control of the LCR, NSFR and instant liquidity ratios. It records the current state, but its ability to forecast future changes in the ratios under external shocks and to assess separately the risk of fund flows through digital channels is limited. This paper addresses this gap by estimating SVAR models that jointly include macroeconomic, monetary and digital factors and by translating the estimates into a stress test and an early warning system.

The paper is structured as follows. Section 2 reviews the literature, Section 3 describes the data and methodology, Section 4 presents and discusses the empirical results, and Section 5 concludes with policy recommendations.[2]

2. Materials and Methods

Four indicators describing different aspects of banking system liquidity were selected as dependent (endogenous) variables. The first is the ratio of highly liquid assets to total assets (HQLA/TA), which shows the relative size of the liquidity cushion on bank balance sheets. The second is the liquidity coverage ratio (LCR), reflecting the ability to cover 30-day net cash outflows under stress with high-quality liquid assets (minimum requirement – 100%). The third is the net stable funding ratio (NSFR), expressing the coverage of long-term assets by stable funding (minimum requirement – 100%). The fourth is the instant liquidity ratio (ILR), measuring a bank's ability to meet current obligations immediately (current minimum requirement – 25%).[3]

The independent variables were divided into two groups. Macroeconomic and financial factors are broad money (M2), the money market interest rate (MMR) and inflation (INF). Two digital factors were selected: the number of remote banking users (RBS), reflecting the degree to which households and firms manage accounts through digital channels, i.e. the potential speed of fund movements; and payment turnover through POS terminals (POS), characterising the intensity of card-based cashless payments and the circulation of funds within the banking system. The logarithmic growth rates of both digital indicators (gRBS, gPOS) enter the model. The system of indicators is presented in Table 1.

Table 1. System of indicators used in the study[4]

Indicator	Symbol	Transformation	Source (cbu.uz)
Highly liquid assets / total assets, %	HQLA/TA	Δ, percentage points	Banking sector liquidity dynamics
Liquidity coverage ratio, %	LCR	Δ, percentage points	Banking sector liquidity dynamics
Net stable funding ratio, %	NSFR	Δ, percentage points	Banking sector liquidity dynamics
Instant liquidity ratio, %	ILR	Δ, percentage points	Banking sector liquidity dynamics
Broad money, UZS bn	M2	100·Δln(M2/CPI)	Monetary aggregates
Money market interest rate, %	MMR	Δ, percentage points	e-GDDS: interest rates
Consumer price index	CPI	INF = 100·ΔlnCPI	Inflation calculator (CPI)
Remote banking users, number	RBS	100·ΔlnRBS	Payment system indicators
Payments via POS terminals, UZS bn	POS	100·Δln(POS/CPI)	Payment system indicators

The data cover the monthly period from January 2017 to December 2025 (108 observations). As the instant liquidity ratio was introduced in 2018, the ILR model is estimated over 2018M1–2025M12. All data are taken from the official website of the Central Bank of the Republic of Uzbekistan.

The empirical strategy comprises several steps: (i) unit root testing with the ADF, PP and KPSS tests; (ii) Johansen cointegration testing; (iii) selection of the optimal lag length using AIC, SC, HQ and FPE criteria; (iv) Granger causality tests; (v) estimation of

the SVAR models in the A-model form Au_t = ε_t with recursive identification, where the matrix A is lower triangular with unit diagonal; (vi) impulse response analysis and forecast error variance decomposition; and (vii) historical and model-based stress testing combined with a threshold-based early warning system. The variable ordering follows economic logic: INF → gM2 → ΔMMR → gRBS → gPOS → liquidity indicator. The price level is treated as the most exogenous variable, money supply and the interest rate represent monetary conditions, and the digital factors represent banking service infrastructure; the liquidity indicator may respond to all shocks within the same month, while affecting other variables only with a lag. Eleven centred monthly dummy variables are included as exogenous regressors to account for seasonality.[5]

3. Result and Discussion

Figure 1 depicts the initial (level) dynamics of the variables. The HQLA/TA ratio rose to 24% at the end of 2017, fell to 8–9% in 2018–2019 as a result of credit expansion and reallocation after the currency liberalisation, recovered in 2021–2022 and stood at 21.1% at the end of 2025.

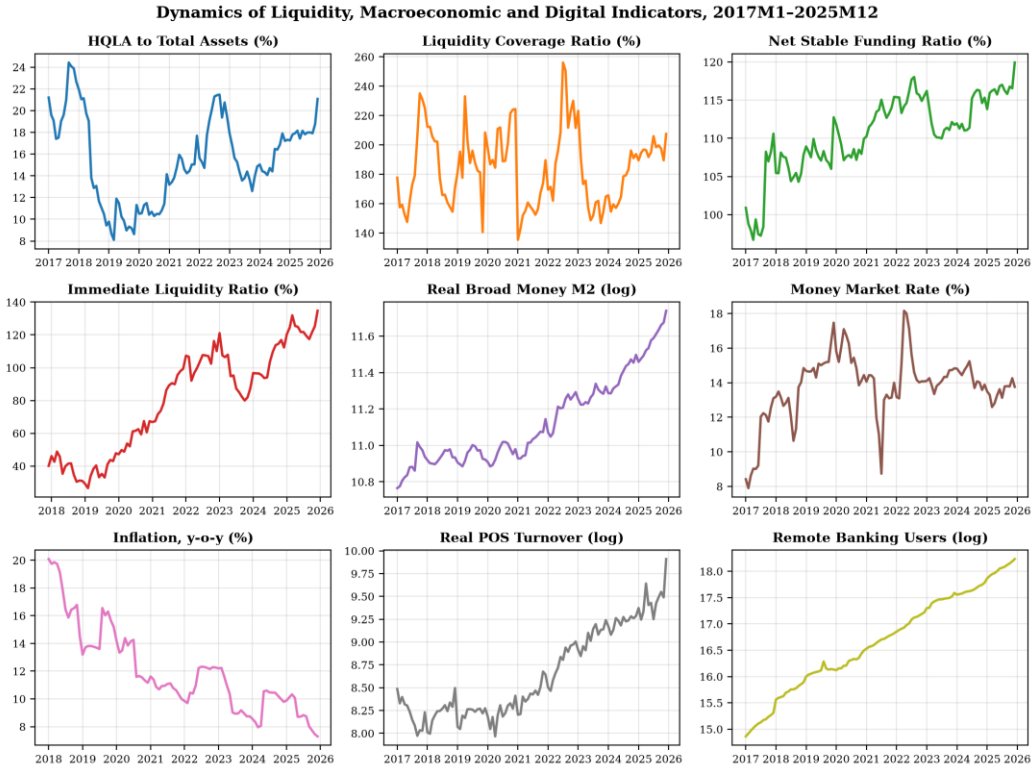


Figure 1. Dynamics of liquidity, macroeconomic and digital indicators (2017M1–2025M12)[6]

The LCR fluctuated between 135% and 255% throughout the period, remaining well above the regulatory requirement; its sharp drop in January 2021 is explained by a change in the calculation methodology. The NSFR increased steadily from 97–100% in 2017 to 119.9% at the end of 2025. The instant liquidity ratio rose from 27–30% in 2019 to 134.7% at the end of 2025, indicating a substantial improvement in banks' immediate payment capacity. Among the digital indicators, the number of remote banking users increased from 2.8 million to 82.9 million, i.e. almost 29-fold, while real POS turnover grew especially rapidly after 2021. Inflation declined from 18–20% in 2017–2018 to 7.3% at the end of 2025, and the money market rate moved between 8% and 18% in line with the policy rate.

The monthly changes in the liquidity indicators average close to zero, but their volatility differs (Table 2): the standard deviation of the change in the LCR is 18.1 percentage points, the highest, while the NSFR is the most stable indicator (1.77 percentage points).

Table 2. Descriptive statistics of variables[7]

Variable	N	Mean	Median	Std. dev.	Min	Max	Skew.	Kurt.	JB (p)
ΔHQLA/TA	108	−0.009	−0.062	1.229	−5.23	3.79	0.14	6.20	46.5 (<0.001)
ΔLCR	108	0.281	0.789	18.087	−89.16	67.86	−0.46	9.76	209.3 (<0.001)
ΔNSFR	108	0.160	0.020	1.769	−5.16	9.84	1.83	11.79	407.8 (<0.001)
ΔILR	96	0.986	0.805	5.306	−14.62	13.86	−0.45	3.64	4.8 (0.090)
gM2	108	0.896	1.141	3.161	−7.35	15.53	0.80	6.33	61.5 (<0.001)
ΔMMR	108	0.045	0.013	0.900	−2.26	4.27	1.34	8.60	173.4 (<0.001)
INF	108	0.938	0.924	0.736	−0.46	4.01	0.70	5.33	33.2 (<0.001)
gPOS	107	1.331	1.141	11.749	−42.45	42.00	−0.10	4.98	17.7 (<0.001)
gRBS	108	3.429	2.872	4.736	−13.14	33.25	3.09	21.45	1704.6 (<0.001)

The ILR increased by 0.99 percentage points per month on average, confirming its steady upward trend. Real money supply grew by 0.90% per month, the number of remote banking users by 3.43% and real POS turnover by 1.33%; average monthly inflation was 0.94%. For most series kurtosis exceeds 3 and the Jarque–Bera test rejects normality, reflecting extreme observations associated with reforms, methodological changes and the 2020 pandemic shock. Skewness (3.09) and kurtosis (21.45) are especially high for gRBS, which is explained by the mass connection to remote services in 2017–2018. Only the distribution of ΔILR is close to normal (p = 0.090).

The pairwise correlations are shown in Figure 2. The correlation coefficient between ΔHQLA/TA and ΔLCR is 0.55, as is that between ΔLCR and ΔNSFR, meaning that an increase in highly liquid assets simultaneously improves short-term and structural liquidity ratios.

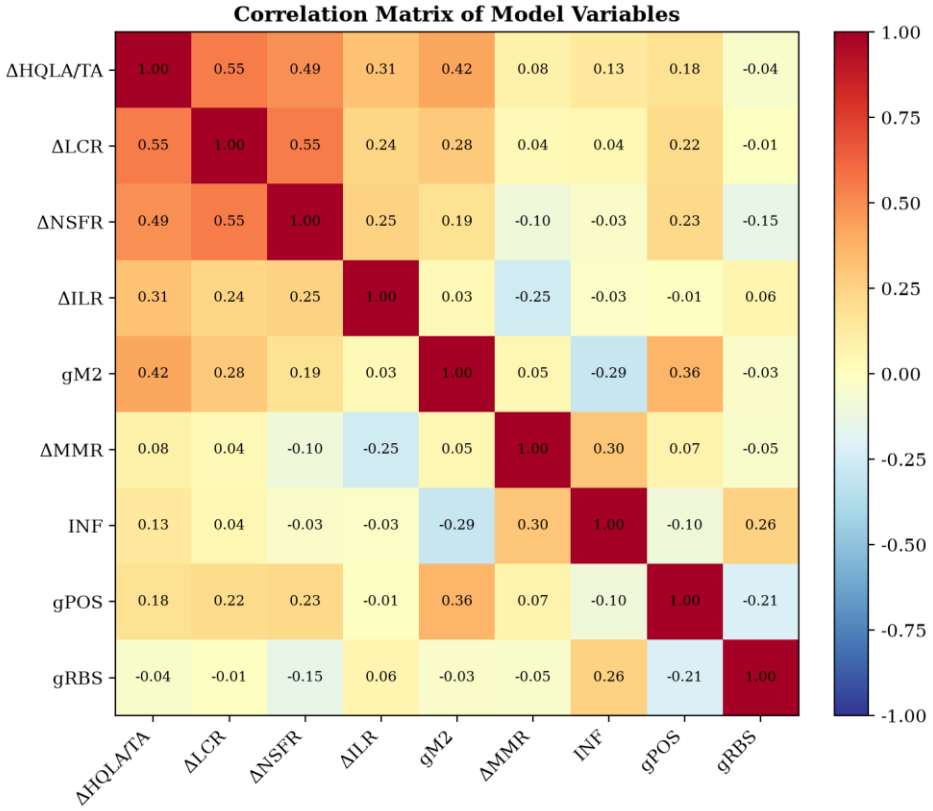


Figure 2. Correlation matrix of model variables[8]

Real money growth is positively correlated with ΔHQLA/TA (0.42) and ΔLCR (0.28), i.e. monetary expansion increases banks' liquid assets. The change in the money market rate is negatively correlated with ΔILR (−0.25): a higher rate makes interbank resources

more expensive and reduces instant liquidity. Inflation is negatively correlated with real money (−0.29) and positively with the money market rate (0.30), reflecting the monetary policy reaction to inflation. Among digital factors, real POS turnover growth is weakly positively associated with the liquidity ratios (0.18–0.23), whereas remote banking growth is negatively correlated with ΔNSFR (−0.15), consistent with the hypothesis that fast fund movements through remote channels may put pressure on the stable funding base. With 96 observations, the 5% significance threshold is approximately $|r| > 0.20$.

In the first step of econometric estimation, the stationarity of the time series was examined using the ADF, PP and KPSS tests (Table 3). In the ADF and PP tests the null hypothesis is a unit root, while in the KPSS test it is stationarity.

Table 3. Stationarity tests (ADF – Augmented Dickey–Fuller; PP – Phillips–Perron; KPSS – Kwiatkowski–Phillips–Schmidt–Shin)[9]

Variable	Form	ADF stat.	ADF p	PP stat.	PP p	KPSS	Conclusion
ln(RM2)	Level	2.061	0.999	1.597	0.998	1.529	I(1)
MMR	Level	−4.076	0.001	−3.261	0.017	0.409	I(0)
ln(CPI)	Level	−2.683	0.077	−5.191	<0.001	1.630	I(1)
ln(RPOS)	Level	1.316	0.997	1.310	0.997	1.507	I(1)
ln(RBS)	Level	−1.458	0.554	−1.490	0.538	1.635	I(1)
HQLA/TA	Level	−2.325	0.164	−1.972	0.299	0.219	I(1)
LCR	Level	−3.814	0.003	−3.512	0.008	0.045	I(0)
NSFR	Level	−1.876	0.344	−1.439	0.563	1.455	I(1)
ILR	Level	−0.349	0.918	−0.340	0.920	1.516	I(1)
gM2	Difference	−1.241	0.656	−10.094	<0.001	0.255	I(0)
ΔMMR	Difference	−5.758	<0.001	−9.557	<0.001	0.128	I(0)
INF	Difference	−2.062	0.260	−5.723	<0.001	0.538	I(0)
gPOS	Difference	−2.848	0.052	−15.142	<0.001	0.521	I(0)
gRBS	Difference	−12.959	<0.001	−12.734	<0.001	0.466	I(0)
ΔHQLA/TA	Difference	−4.266	<0.001	−9.133	<0.001	0.252	I(0)
ΔLCR	Difference	−11.777	<0.001	−13.252	<0.001	0.034	I(0)
ΔNSFR	Difference	−10.883	<0.001	−12.084	<0.001	0.032	I(0)
ΔILR	Difference	−6.012	<0.001	−11.083	<0.001	0.084	I(0)

The level series ln(RM2), ln(RPOS), ln(RBS), HQLA/TA, NSFR and ILR are non-stationary: the ADF and PP tests do not reject a unit root and the KPSS statistic exceeds the 5% critical value (0.463). The money market rate and the LCR are stationary in levels. For first differences (growth rates), the PP test rejects the unit root for all series at the 1% level and the KPSS statistics are below the critical value. The weak ADF results for gM2 and INF are associated with seasonal fluctuations, and the PP and KPSS tests, robust to autocorrelation and heteroskedasticity, confirm their stationarity. Thus the variables are mainly I(1), their growth rates are I(0), and their use in differences in the SVAR model is justified.

The existence of a long-run equilibrium relationship between level variables was examined with the Johansen cointegration test. For each liquidity indicator a six-dimensional system consisting of ln(CPI), ln(RM2), MMR, ln(RBS), ln(RPOS) and the corresponding liquidity indicator was considered (Table 4).

Table 4. Johansen cointegration test (Trace and Maximum Eigenvalue)[10]

System	H0	Trace	5% c.v.	Max-Eigen	5% c.v.
HQLA/TA	r = 0	99.46*	95.75	30.27	40.08

System	H0	Trace	5% c.v.	Max-Eigen	5% c.v.
	r ≤ 1	69.18	69.82	24.53	33.88
	r ≤ 2	44.66	47.85	18.64	27.59
LCR	r = 0	115.25*	95.75	42.44*	40.08
	r ≤ 1	72.82*	69.82	29.83	33.88
	r ≤ 2	42.98	47.85	21.43	27.59
NSFR	r = 0	98.82*	95.75	33.49	40.08
	r ≤ 1	65.32	69.82	24.81	33.88
	r ≤ 2	40.51	47.85	18.94	27.59
ILR	r = 0	82.95	95.75	32.65	40.08
	r ≤ 1	50.30	69.82	16.75	33.88
	r ≤ 2	33.54	47.85	15.89	27.59

Note: * denotes rejection of the null hypothesis at the 5% level.

The trace statistic rejects r = 0 in the HQLA/TA system (99.46 > 95.75), indicates two cointegrating vectors in the LCR system (72.82 > 69.82 for r ≤ 1) and one vector in the NSFR system. The maximum eigenvalue statistic confirms one cointegrating relationship only in the LCR system (42.44 > 40.08). No cointegration is found in the ILR system. Evidence of a long-run equilibrium is therefore mixed and weak: the trace tests only marginally exceed the critical values, while the max-eigen tests mostly fail to reject the null. For this reason, the analysis focuses on short-run dynamics, the SVAR model is estimated in stationary differences, and the VECM approach is retained as an alternative robustness tool.

Table 5. Optimal lag length selection (ΔLCR model)[11]

Lag	AIC	SC (BIC)	HQ	FPE
0	13.348	15.236*	14.112*	631,293
1	13.267*	16.098	14.412	591,973*
2	13.568	17.343	15.095	828,123
3	13.603	18.322	15.512	909,803
4	13.486	19.148	15.777	886,566
5	13.721	20.327	16.394	1,282,388
6	13.942	21.492	16.997	1,935,260
7	13.998	22.491	17.435	2,664,131
8	14.024	23.461	17.842	3,927,862

Note: * indicates the lag order selected by the criterion.

The SC and HQ criteria reach their minimum at p = 0, while AIC and FPE point to p = 1 (Table 5). In the HQLA/TA and NSFR models AIC selects the largest lag (8), which leads to over-parameterisation due to the sharp increase in the number of parameters. Taking into account the lagged transmission of monetary policy in monthly data, the need for residuals free of autocorrelation and the requirement to preserve degrees of freedom in a sample of 105 observations, p = 2 lags were chosen for all models. This choice ensured white-noise residuals over short horizons according to the portmanteau test.

Granger causality tests assess the ability of the factors to predict the liquidity indicators (Table 6).

Table 6. Granger causality test results (F-statistic, p-value)[12]

Factor	→ ΔHQLA/TA	→ ΔLCR	→ ΔNSFR	→ ΔILR	Reverse: ΔLCR →	Reverse: ΔNSFR →
INF	0.26 (0.772)	3.31 (0.037)**	7.06 (<0.001)***	1.94 (0.145)	0.21 (0.813)	0.96 (0.383)

Factor	→ ΔHQLA/TA	→ ΔLCR	→ ΔNSFR	→ ΔILR	Reverse: ΔLCR →	Reverse: ΔNSFR →
gM2	1.15 (0.317)	2.78 (0.063)*	4.97 (0.007)***	3.32 (0.037)**	0.88 (0.416)	0.68 (0.508)
ΔMMR	2.40 (0.092)*	0.87 (0.418)	5.44 (0.005)***	0.35 (0.703)	1.11 (0.332)	3.03 (0.049)**
gRBS	0.20 (0.820)	2.55 (0.079)*	0.55 (0.575)	0.39 (0.679)	0.15 (0.864)	0.17 (0.847)
gPOS	0.25 (0.776)	0.18 (0.832)	0.87 (0.422)	0.56 (0.570)	0.83 (0.435)	0.07 (0.929)
Digital factors jointly	0.20 (0.939)	1.41 (0.231)	0.82 (0.515)	0.47 (0.760)		
Macro factors jointly	1.55 (0.161)	2.29 (0.034)**	5.52 (<0.001)***	2.06 (0.057)*		

Note: *, , * denote significance at the 1%, 5% and 10% levels, respectively.

The strongest causal relationships are found in the NSFR model: inflation ($F = 7.06$, $p < 0.001$), real money supply ($p = 0.007$) and the money market rate ($p = 0.005$) Granger-cause changes in the NSFR, and the joint effect of macroeconomic factors is highly significant ($F = 5.52$, $p < 0.001$). In the LCR model, inflation is a Granger cause at the 5% level ($p = 0.037$), while real money ($p = 0.063$) and growth in remote banking users ($p = 0.079$) are Granger causes at the 10% level. This result shows that the expansion of digital channels has a statistically significant effect on the short-term liquidity ratio. Changes in the ILR are driven by real money ($p = 0.037$), and changes in HQLA/TA only by the money market rate at the 10% level ($p = 0.092$). In the reverse direction, causality from liquidity indicators to factors is almost absent; only ΔNSFR Granger-causes the money market rate ($p = 0.049$), meaning that banks' structural liquidity position feeds back into supply and demand in the interbank market. POS turnover is not a Granger cause in any model, i.e. card payments are mainly a redistribution within the banking system and do not change the overall level of liquidity. The p-values are visualised in Figure 3.

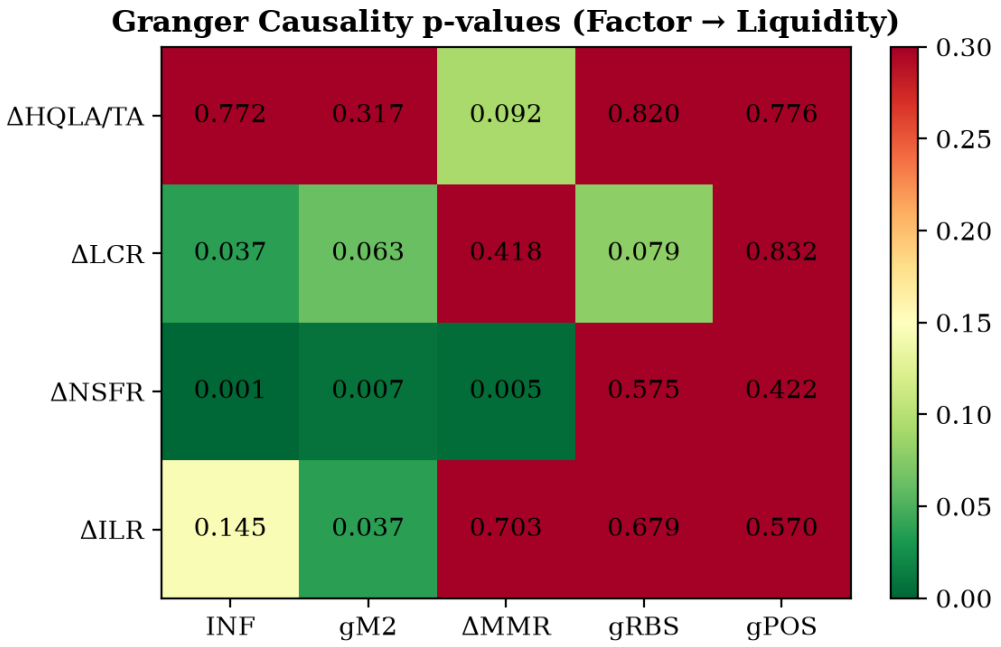


Figure 3. Granger causality test p-values (factor → liquidity)[13]

The structural shock effects estimated with the recursively identified SVAR models are summarised in Table 7. A positive real money shock significantly increases almost all liquidity indicators within the same month: HQLA/TA by 0.54 percentage points, LCR by

3.85 percentage points and NSFR by 0.37 percentage points; for the ILR, the 12-month cumulative effect of 3.39 percentage points is significant.

Table 7. Effects of structural shocks on liquidity indicators (percentage points)[14]

Model / Shock	h = 0	h = 1	h = 2	h = 3	12-month cumulative
Dependent variable: ΔHQLA/TA					
INF	−0.139	0.046	0.182	0.105	0.318
gM2	0.544*	−0.123	0.119	−0.023	0.504
ΔMMR	0.004	0.158	0.251	0.025	0.490
gRBS	−0.139	0.011	−0.114	−0.044	−0.370
gPOS	0.039	0.073	−0.083	0.016	0.023
Dependent variable: ΔLCR					
INF	−1.060	1.791	2.685	1.228	5.170
gM2	3.848*	0.116	2.829	−1.410	5.112
ΔMMR	−1.021	0.930	3.336	0.395	3.689
gRBS	0.156	−1.788	−3.853*	0.794	−5.135
gPOS	0.981	−1.343	0.318	−0.040	−0.434
Dependent variable: ΔNSFR					
INF	−0.006	−0.339*	0.419*	0.256*	0.376
gM2	0.366*	−0.244	0.470*	−0.083	0.421
ΔMMR	−0.074	0.068	0.499*	0.006	0.528*
gRBS	−0.353*	0.119	−0.122	−0.030	−0.437
gPOS	−0.059	−0.147	0.111	0.018	−0.140
Dependent variable: ΔILR					
INF	−0.686	0.329	0.335	0.205	0.216
gM2	1.091	1.112	1.167	0.084	3.388*
ΔMMR	−1.557*	0.352	0.528	0.635	−0.199
gRBS	−0.501	0.596	−0.231	−0.008	−0.302
gPOS	0.127	0.406	−0.280	0.546	0.610

Note: * denotes significance at the 5% level (95% confidence interval excludes zero).

An increase in the money market rate immediately reduces the ILR by 1.56 percentage points, as more expensive interbank resources constrain instant liquidity; its effect on the NSFR becomes positive (0.50) after two months, i.e. higher rates strengthen the stable funding base by attracting term deposits. An inflation shock first affects the NSFR negatively (−0.34) and then positively in the second and third months, which is explained by the lagged effect of monetary tightening in response to rising prices. The most important result regarding digital factors is the negative effect of growth in remote banking users: it immediately reduces the NSFR by 0.35 percentage points and the LCR by 3.85 percentage points after two months, and its 12-month cumulative effect is negative in all four models. This indicates that digitalisation increases the mobility of customer funds, reduces the "stickiness" of the deposit base and requires banks to hold additional liquidity buffers. POS turnover shocks are insignificant in all models.

The impulse response functions (Figures 4–7) show the 24-month responses of the liquidity indicators to one-standard-deviation structural shocks with 95% confidence intervals.

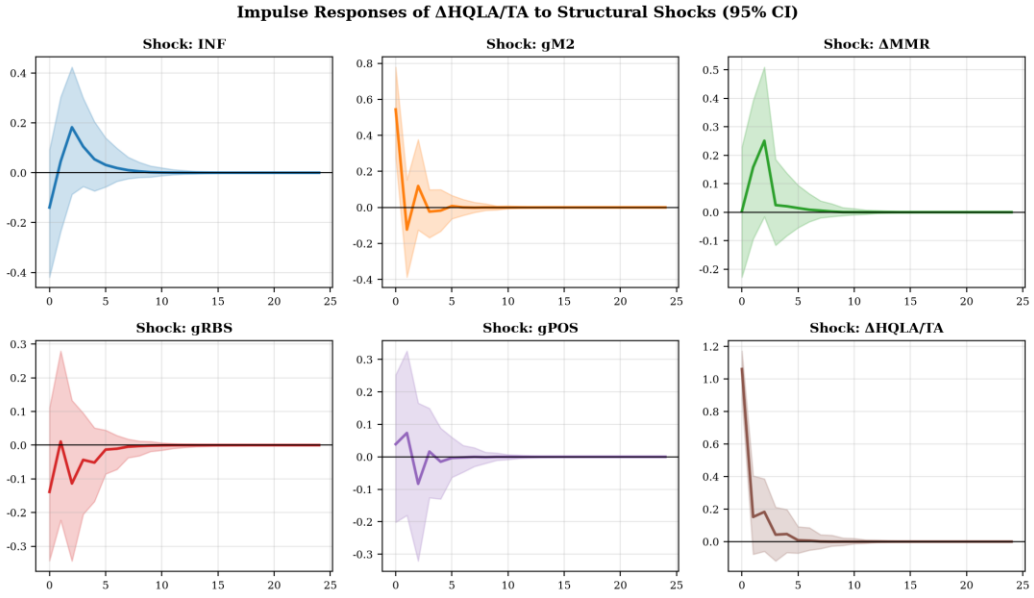


Figure 4. Impulse responses of ΔHQLA/TA to structural shocks[15]

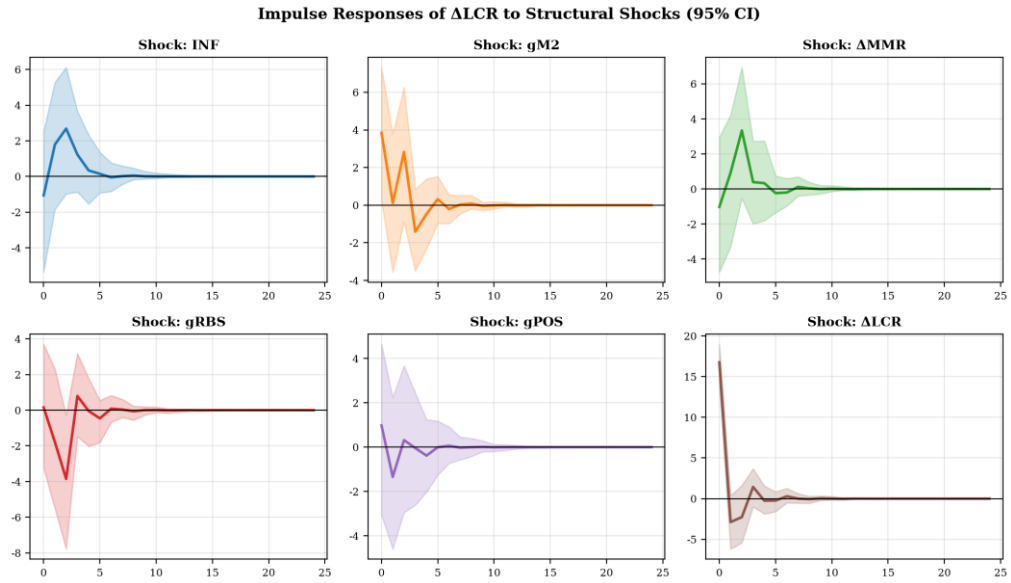


Figure 5. Impulse responses of ΔLCR to structural shocks[16]

In all models the responses die out within 6–8 months, indicating that the liquidity indicators absorb shocks quickly and that the banking system manages liquidity flexibly. In the ΔHQLA/TA model the real money shock produces a significant positive response of 0.54 percentage points in the first month, and the money market rate shock has a positive effect of 0.25 percentage points in the second month, whereas the remote banking shock generates a negative response (−0.11) in the second month. In the ΔLCR model, the money supply shock produces an immediate positive response of 3.85 percentage points, while the remote banking shock yields a significant negative response of 3.85 percentage points in the second month – the channel through which digitalisation affects short-term liquidity most visibly.

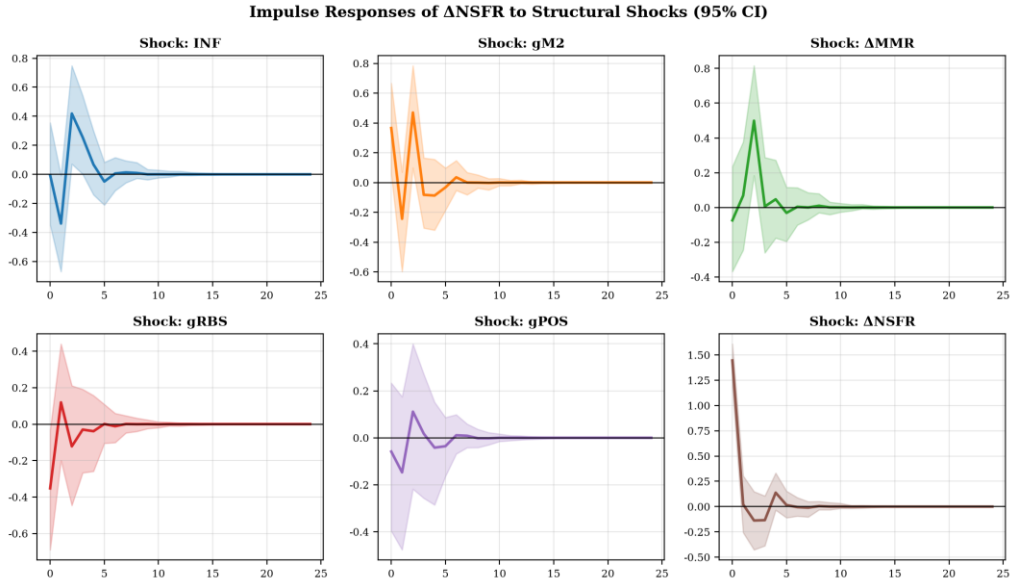


Figure 6. Impulse responses of ΔNSFR to structural shocks[17]

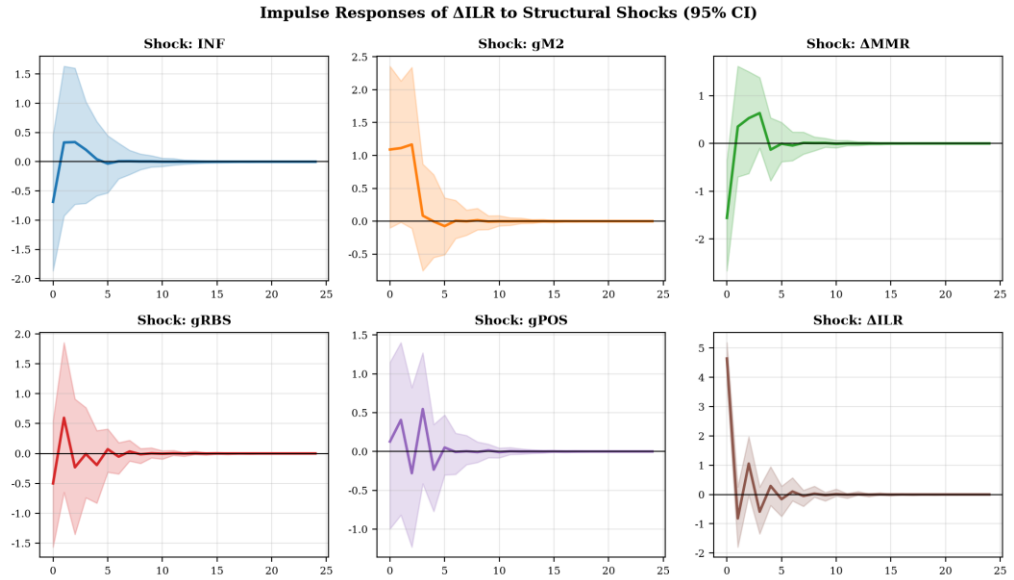


Figure 7. Impulse responses of ΔILR to structural shocks

The ΔNSFR model has the largest number of significant responses: the response to an inflation shock is negative in the first month and positive in the second and third months, and the cumulative effect of the money market rate shock (0.53 percentage points) is significant. In the ΔILR model, the money market rate shock produces an immediate negative response of 1.56 percentage points, while the cumulative effect of the money supply shock reaches 3.39 percentage points. The confidence intervals of the responses to POS turnover shocks include zero in all models.

The forecast error variance decomposition shows what share of the variability of each liquidity indicator is explained by shocks to different factors (Table 8 and Figure 8).

Table 8. Variance decomposition of liquidity indicators (%)[18]

Indicator	Horizon (months)	INF	gM2	ΔMMR	gRBS	gPOS	Own shock
ΔHQLA/TA	1	1.3	20.2	0.0	1.3	0.1	77.0
	3	3.2	19.2	5.2	1.9	0.8	69.7
	6	4.1	18.9	5.2	2.2	0.8	68.9
	12	4.1	18.9	5.2	2.2	0.8	68.8

Indicator	Horizon (months)	INF	gM2	ΔMMR	gRBS	gPOS	Own shock
	24	4.1	18.9	5.2	2.2	0.8	68.8
ΔLCR	1	0.4	5.0	0.3	0.0	0.3	94.0
	3	3.2	6.3	3.6	5.0	0.8	81.1
	6	3.6	6.8	3.6	5.1	0.8	80.1
	12	3.6	6.8	3.6	5.1	0.8	80.1
	24	3.6	6.8	3.6	5.1	0.8	80.1
ΔNSFR	1	0.0	5.7	0.2	5.3	0.1	88.7
	3	8.9	12.7	7.9	4.7	1.1	64.6
	6	10.7	12.6	7.7	4.6	1.2	63.2
	12	10.7	12.7	7.7	4.6	1.2	63.1
	24	10.7	12.7	7.7	4.6	1.2	63.1
ΔILR	1	1.8	4.6	9.4	1.0	0.1	83.2
	3	2.2	12.0	9.0	2.1	0.8	73.9
	6	2.2	11.6	9.9	2.1	1.9	72.3
	12	2.2	11.6	9.9	2.1	1.9	72.3
	24	2.2	11.6	9.9	2.1	1.9	72.3

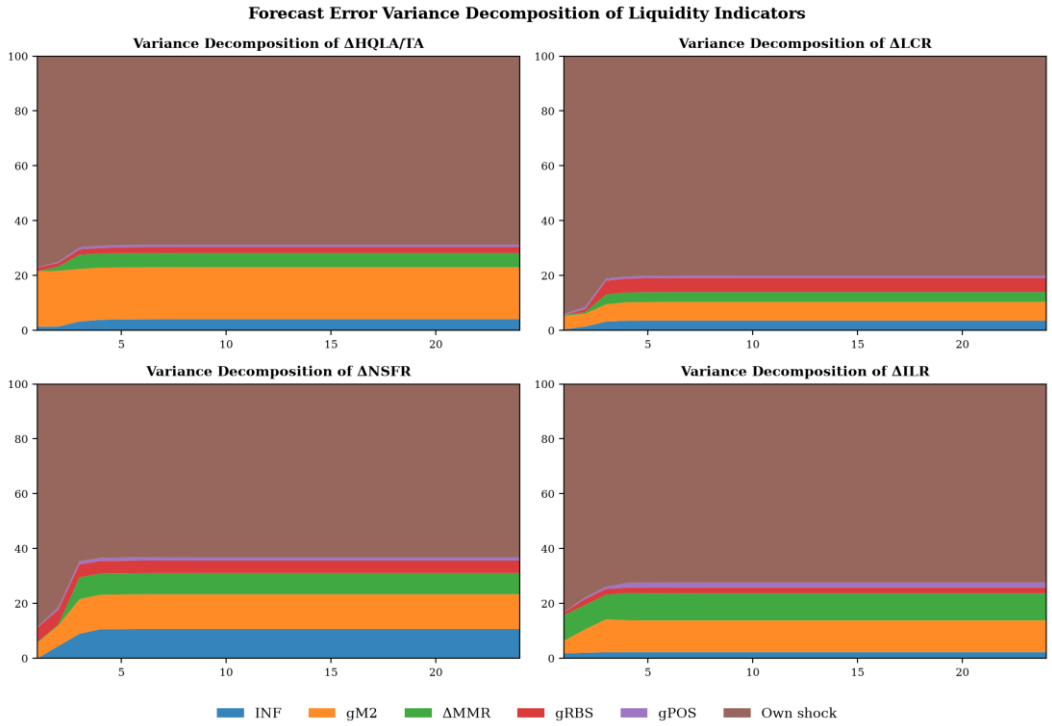


Figure 8. Forecast error variance decomposition of liquidity indicators[19]

In the first month most of the variability (77–94%) is due to the indicator's own shocks, but over 3–6 months the share of external factors increases and stabilises at the 12-month horizon. At that horizon, external factors explain 31.2% of HQLA/TA variability, 19.9% for the LCR, 36.9% for the NSFR and 27.7% for the ILR. The most important external factor is real money supply: its contribution amounts to 18.9% for HQLA/TA, 12.7% for the NSFR and 11.6% for the ILR. Inflation explains 10.7% of NSFR variability and the money market rate 9.9% of ILR variability. The joint contribution of digital factors ranges from 3.0% (HQLA/TA) to 5.9% (LCR) and 5.8% (NSFR), with the share of remote banking being 3–6 times higher than that of POS turnover. The contribution of remote banking to LCR

variability (5.1%) exceeds that of the money market rate and inflation, showing that digital channels have become an independent source of short-term liquidity risk.

The estimated SVAR models can serve as the quantitative basis of a liquidity monitoring system. On this basis a two-stage approach is proposed: a historical and model-based stress test and a threshold-based early warning system. Under the historical scenario, the worst 3-month and 12-month declines observed in 2017–2025 were applied to the December 2025 levels. Under the model-based scenario, a 2-standard-deviation negative real money shock (monetary contraction) and a 2-standard-deviation surge in remote banking users (rapid outflow of funds through digital channels) were assumed to occur simultaneously, with the 12-month cumulative effect computed from the impulse responses (Table 9).

Table 9. Stress test results for liquidity indicators (%)

Indicator	2025M12 level	Minimum requirement	Historical: worst 3-month	Historical: worst 12-month	Model scenario (12 months)	Conclusion
HQLA/TA	21.1	—	13.8	7.7	19.3	Buffer sufficient
LCR	207.5	100	121.3	103.2	187.0	Buffer 3.2 p.p. at 12 months
NSFR	119.9	100	114.2	112.2	118.2	Stable
ILR	134.7	25	114.1	100.4	127.3	Stable

Even under the most severe historical 12-month scenario, the LCR remains at 103.2%, the NSFR at 112.2% and the ILR at 100.4%, above the regulatory requirements. The LCR buffer, however, shrinks to only 3.2 percentage points, making it the weakest link. Under the model-based scenario the LCR falls by 20.5 percentage points, HQLA/TA by 1.8 percentage points and the ILR by 7.4 percentage points, but all ratios remain in the safe zone. Thus the liquidity buffer at the end of 2025 is sufficiently robust to macroeconomic and digital shocks, but a repetition of historical extreme events would bring the LCR buffer close to a critical level.

For the early warning system, the signal approach based on the methodology of Kaminsky, Lizondo and Reinhart (1998) was applied: a warning signal is issued if the 3-month change in a liquidity indicator falls below −1.5 times its historical standard deviation (Table 10).

Table 10. Early warning system signals (3-month change < −1.5σ)[20]

Indicator	Threshold (p.p.)	Number of signals	Signal months
HQLA/TA	−3.5	6	2017M4; 2018M6–M8; 2023M2–M3
LCR	−41.4	5	2019M11; 2021M1–M3; 2023M4
NSFR	−4.2	2	2020M4; 2023M4
ILR	−13.1	2	2023M4; 2023M7

During the analysis period, 6 signals were recorded for HQLA/TA, 5 for the LCR and 2 each for the NSFR and ILR. The signals correspond to three major stress episodes: the contraction of liquid assets in mid-2018 (credit expansion period), the decline in the LCR in early 2021 (methodological change and post-pandemic reallocation) and the simultaneous decline of all four indicators in April–July 2023. The simultaneous appearance of signals for all four indicators in April 2023 is a reliable indicator of systemic liquidity pressure. No signals were recorded in 2024–2025, confirming the stability of the current liquidity position.

The assessment also reveals several data limitations. First, the methodology of the liquidity indicators has changed several times (the transition from "highly liquid assets" to "high-quality liquid assets" and the increase of the minimum instant liquidity requirement from 10% to 25%), causing structural breaks in long series. Second, statistics on digital services are largely limited to the number of users and card transactions; indicators such as the volume of transfers through remote channels or the opening and closing of deposits through digital channels are not available. Third, the data are aggregated at the banking system level, and monthly liquidity ratios of individual banks are not publicly disclosed for panel analysis.

4. Conclusion

The SVAR analysis of the Uzbek banking system over 2017–2025 leads to the following conclusions and recommendations. First, real money supply is the main external driver of bank liquidity, explaining 7–19% of the variability of liquidity indicators. Consequently, the Central Bank's liquidity management operations and reserve requirements are the instruments transmitted most rapidly to banks' liquidity positions. Second, the rapid expansion of remote banking services has a negative cumulative effect on liquidity in all models and explains 5.1% of LCR variability. This calls for taking the risk of "rapid deposit outflows" through digital channels into account by differentiating outflow rates in the LCR calculation. Third, POS turnover has no significant effect on liquidity, as card payments are mainly redistributed within the banking system. Fourth, the liquidity buffer at the end of 2025 is robust to macroeconomic and digital shocks, but under a repetition of the worst historical 12-month episode the LCR buffer would decline to 3.2 percentage points. It is recommended that an SVAR-based macro stress-testing module and a signal system based on 3-month changes be introduced into the practice of the Central Bank and commercial banks. Fifth, extending digital banking statistics with indicators of transfer volumes through remote channels and deposit flows would substantially improve the accuracy of liquidity risk forecasting. Future research could use bank-level panel data and higher-frequency transaction data to refine the identification of digital liquidity shocks.

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