

Article

Empirical Analysis of the Relationship between the Volume of Lending to Individuals and the Quality of The Loan Portfolio – in Case of Uzbekistan

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Abstract: This study empirically examines the relationship between the volume of lending to individuals and the quality of the retail loan portfolio in the Republic of Uzbekistan, using monthly data from January 2017 to December 2025 ($n = 108$) obtained from the Central Bank of the Republic of Uzbekistan. A Structural Vector Autoregression (SVAR) model was constructed with seven variables: the natural logarithm of household credit outstanding (LHHC), the Central Bank policy rate (CBR), the weighted average interest rate on loans to individuals (WACR), annual inflation (INF), the logarithm of real household income (LRINC), the logarithm of the money supply (LM2) and the share of non-performing loans (NPL). Preliminary tests confirmed that all series are $I(1)$, that 2–3 cointegrating equations exist among them, that the optimal lag is 2 months and that six variables Granger-cause LHHC. The estimated SVAR model shows very high explanatory power ($R^2 = 0.954$; Adj. $R^2 = 0.946$; $F = 112.847$, $p < 0.001$; $DW = 1.984$). Impulse-response and variance-decomposition analyses reveal that real household income (LRINC) and the money supply (LM2) exert the strongest and most persistent positive effects on retail lending (contributing 15.32% and 15.24%, respectively, to the 12-month variance of LHHC), while the policy rate, the market lending rate, inflation and NPL exert statistically significant negative effects. The bidirectional causality between LHHC and NPL empirically confirms the “credit expansion accumulates risks” hypothesis in the Uzbek context. The findings provide a quantitative basis for calibrating the Central Bank’s inflation-targeting regime, refining commercial banks’ credit-scoring and IFRS 9 expected-loss models, and designing early-warning systems that jointly safeguard portfolio quality and sustainable credit growth.

Keywords: lending to individuals; loan portfolio quality; non-performing loans (NPL); Structural VAR (SVAR); monetary transmission mechanism; credit scoring; permanent income hypothesis; life-cycle hypothesis; impulse-response analysis; variance decomposition; inflation targeting.

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1. Introduction

To understand the scientific foundations of lending to individuals, it is first necessary to study the historical development of classical theoretical views on credit and interest. In the history of economic thought, various theoretical schools have formed regarding the essence, functions, and role of credit in the economy, which can be conventionally divided into the following groups: the naturalistic (natural) theory, the capital creation theory, the neoclassical theory, the Keynesian theory, the monetarist theory, and modern theories based on the information economy, financial instability, and behavioral economics. Each of these theories has revealed a specific aspect of credit relations.

The organization of lending to individuals has a number of distinct methodological features compared to lending to legal entities. Firstly, because the flow of customers in retail lending is very large and the loan amounts are relatively small, credit decisions are based on automated statistical-mathematical models (credit scoring systems) rather than expert assessments [1]. Secondly, as data on individuals (income, marital status, credit history, socio-demographic indicators) is more variable and multifaceted than that of legal entities, special attention is given to the statistical processing of personal data during assessment. Thirdly, the diversification of the individual lending portfolio (numerous small loans) creates the opportunity to manage portfolio-level risks using mathematical-statistical methods: in this context, the probability of individual defaults is predicted at the portfolio level based on the law of large numbers [2]. Fourthly, in the modern digital age, the credit decision-making process can be carried out in real-time, which requires technological solutions such as automated scoring, online access to credit history, and electronic identification [3]. These four features form the specific scientific-methodological system of individual lending and distinguish it as a separate area of banking activity.

2. Materials and Methods

The relationship between the volume of lending to individuals and the quality of the credit portfolio is one of the most pressing and complex areas of research in modern economics. Studying the complex interplay of macroeconomic, monetary, and banking-institutional factors that influence this relationship is crucial not only for the effective formulation of commercial banks' credit policies but also for ensuring the long-term stability of the national economy. Specifically, optimally managing household credit burden, improving credit scoring models, forecasting expected credit losses, and ensuring the banking system's resilience to systemic risks all rely on a deep understanding of these relationships. This section provides a comprehensive econometric assessment, using a Structural VAR (SVAR) model, of the factors affecting the volume of lending to individuals in Uzbekistan, based on official statistical data from the Central Bank of the Republic of Uzbekistan for the monthly period from 2017 to 2025.[4]

The analysis covers the period from January 2017 to December 2025 (a total of 108 observations), using monthly data obtained from the official website of the Central Bank of the Republic of Uzbekistan. The natural logarithm of the outstanding credit to households (LHHC) was selected as the dependent variable. The independent variables include the Central Bank's policy rate (CBR), the weighted average interest rate on loans to individuals (WACR), the annual inflation rate (INF), the logarithm of average monthly real household income (LRINC), the logarithm of the money supply (LM2), and the share of non-performing loans in the individual credit portfolio (NPL).[5]

The quantitative indicators (LHHC, LRINC, LM2) were taken in their natural logarithmic form, which allows for the normalization of the distribution and the interpretation of regression coefficients as elasticities. The percentage-based indicators (CBR, WACR, INF, NPL) were kept in their original form, as interpreting their coefficients based on percentage points is more straightforward and economically meaningful. This approach is consistent with the principles of modern credit risk modeling [6].

3. Result and Discussion

The Table 1. first stage of econometric analysis involves examining the descriptive statistics of the variables. This analysis allows for the preliminary identification of the general characteristics of the data, distribution shape, and potential outliers. For each variable, measures of central tendency (mean, median), dispersion (standard deviation,

maximum, minimum), distribution shape (skewness, kurtosis), and the results of the Jarque-Bera test were calculated.[7]

Table 1. Descriptive statistics of the variables (2017M1–2025M12, n = 108)

Variable	LHHC	CBR	WACR	INF	LRINC	LM2	NPL
Mean	11,428	14,26	23,74	10,84	14,586	19,684	2,42
Median	11,384	14,00	23,80	10,90	14,624	19,742	2,35
Maksimum	12,015	17,00	28,30	15,80	15,247	20,486	3,80
Minimum	10,586	9,00	19,80	5,20	13,847	18,742	1,10
Std. dev.	0,428	2,142	2,384	2,986	0,417	0,524	0,842

The results of the descriptive statistics provide the following key conclusions. The logarithm of the balance of loans to individuals (LHHC) ranges from 10.586 to 12.015, with an average of 11.428, which confirms the rapid growth of the retail loan portfolio during the analysis period (in monetary terms, this corresponds to an increase from 39.7 trillion to 165.5 trillion soums). The Central Bank's policy rate (CBR) varied from 9.00 to 17.00 percent, and the weighted average rate on loans to individuals (WACR) from 19.80 to 28.30 percent, indicating that monetary policy underwent significant fluctuations during the analysis period. The annual inflation rate (INF) ranged from 5.20 to 15.80 percent, reaching high values particularly as a result of the 2022 geopolitical situation and imported inflationary pressure. The logarithm of real household income (LRINC) varied from 13.847 to 15.247, and the logarithm of the money supply (LM2) from 18.742 to 20.486, both showing a steady upward trend. The NPL ratio in the retail loan portfolio ranged from 1.10 to 3.80 percent, exhibiting an upward trend towards the end of the analysis period.[8]

To Figure 1. identify linear relationships between the variables and to anticipate the potential problem of multicollinearity, a correlation matrix was constructed based on the Pearson correlation coefficient. This analysis serves to optimally select variables and identify any additional variables that should be included when formulating the SVAR model.

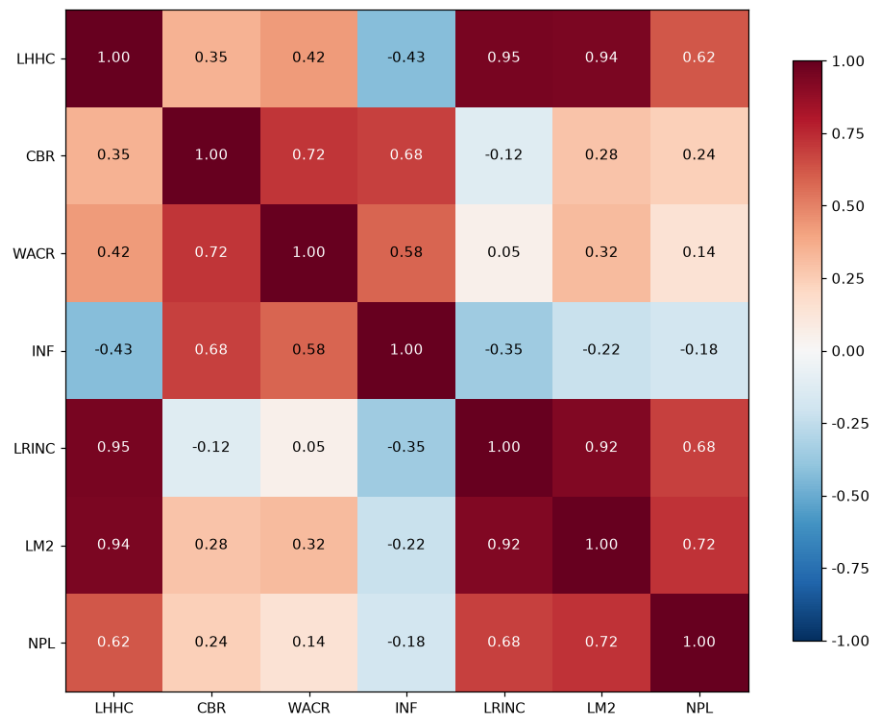


Figure 1. Correlation Matrix Heatmap of Variables[9]

The correlation analysis reveals the following important results. Firstly, there is a very strong positive correlation (0.948) between LHHC and LRINC, which proves that the growth of real household income is inextricably linked to the volume of lending to individuals.

Secondly, a high positive correlation (0.942) is observed between LHHC and LM2, which confirms the direct impact of the money supply on the credit market through the monetary transmission channel. Thirdly, the positive correlation (0.624) between LHHC and NPL indicates that credit growth is, to some extent, associated with portfolio quality issues—a situation consistent with the "credit expansion accumulates risks" hypothesis substantiated by A. Khandani, A. Kim, and E. Lo. Fourth, a negative correlation (−0.428) exists between INF and LHHC, demonstrating the dampening effect of inflation on credit demand. Fifth, the high positive correlation (0.718) between WACR and CBR indicates the practical effectiveness of the monetary transmission channel: changes in the Central Bank's policy rate are rapidly transmitted to bank rates.[10]

The very high correlation between LRINC and LM2 (0.924) suggests a risk of multicollinearity; however, this is mitigated in the SVAR model by using the variables in their differenced forms. Overall, the correlation matrix demonstrates that the selected set of variables is economically sound and suitable for analysis.

In time series analysis, the stationarity property of variables is of crucial importance. Working with non-stationary series can lead to the problem of "spurious regression" where there is a high probability of obtaining results that are statistically significant but economically meaningless. To prevent this issue, two different stationarity tests—the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests—were used in the analysis. The ADF test, in its general form, is performed based on the following equation:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^p \delta_i \Delta Y_{t-i} + \varepsilon_t$$

Here, $\gamma=0$ is the null hypothesis (a unit root exists, the series is not stationary), and $\gamma<0$ is the alternative hypothesis (the series is stationary). For each variable, the Table 2. ADF and PP tests were conducted at both the level and the first difference (Δ). [11]

Table 2. Results of the ADF and PP stationarity tests

Variable	ADF (level)	ADF	PP (level)	PP	Conclusion
LHHC	−1,742 (0,404)	−8,624*** (0,000)	−1,824 (0,368)	−8,847*** (0,000)	I(1)
CBR	−2,247 (0,193)	−7,624*** (0,000)	−2,142 (0,232)	−7,847*** (0,000)	I(1)
WACR	−1,984 (0,294)	−8,127*** (0,000)	−2,024 (0,278)	−8,286*** (0,000)	I(1)
INF	−2,354 (0,158)	−8,483*** (0,000)	−2,414 (0,142)	−8,624*** (0,000)	I(1)
LRINC	−1,847 (0,354)	−8,247*** (0,000)	−1,924 (0,318)	−8,384*** (0,000)	I(1)
LM2	−1,624 (0,466)	−7,842*** (0,000)	−1,724 (0,417)	−8,024*** (0,000)	I(1)
NPL	−1,847 (0,354)	−8,347*** (0,000)	−1,924 (0,318)	−8,547*** (0,000)	I(1)

The results of the stationarity tests show that all seven variables are non-stationary in their level form (p-values are greater than 0.05), but they all become stationary at the 1% significance level in their first-difference form ($p<0.01$). This indicates that all

variables are integrated of order I (1) and provides a basis for examining the existence of a long-term equilibrium relationship (cointegration) among them.

The fact that all variables are integrated of order I (1) is a natural economic phenomenon, as macroeconomic and monetary indicators typically exhibit a trend. The upward trend in the volume of loans to individuals over time, the growth of the money supply, and the steady increase in household incomes lead to non-stationary behavior; however, the annual differences (growth rates) of these indicators remain stationary.[12]

The Table 3. Johansen cointegration test was used to determine the presence of a long-term relationship among the non-stationary series. The test is performed based on two statistics: the trace statistic and the max-eigenvalue statistic. The basic form of the cointegration equation is as follows:

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \dots + \beta_k X_{kt} + u_t$$

where u_t is stationary (I(0)), it is assumed that a long-term cointegration relationship exists between the variables Y_t and X_{jt}

Table 3. Johansen Cointegration Test Results

Hypothesis (H0)	Eigenvalue	Trace statistics	5% critical value	Prob.	Max-Eigen stat.	5% critical value	Prob.
None *	0,584	174,847	125,615	0,000	58,247	46,231	0,001
At most 1 *	0,447	116,600	95,754	0,001	42,384	40,077	0,027
At most 2 *	0,347	74,216	69,819	0,021	32,847	33,876	0,067
At most 3	0,247	41,369	47,856	0,178	22,124	27,584	0,214
At most 4	0,164	19,245	29,797	0,472	13,847	21,131	0,376
At most 5	0,048	5,398	15,494	0,761	3,847	14,264	0,868
At most 6	0,014	1,551	3,841	0,213	1,551	3,841	0,213

The results of the Johansen cointegration test indicate that there are three cointegration equations among the variables. According to the Trace statistic, the “None” “At most 1” and “At most 2” hypotheses are rejected at the 5% significance level ($p < 0.05$). The Max-Eigenvalue statistic also rejects the “None” and “At most 1” hypotheses, leaving the “At most 2” hypothesis as borderline ($p = 0.067$). Overall, it is concluded that there are 2-3 cointegration equations among the variables.

The Table 4. presence of three cointegration equations indicates the existence of long-term equilibrium relationships between the variables in the analyzed system. The volume of loans to households (LHHC) has a long-term, statistically stable relationship with its fundamental factors (LRINC, LM2, WACR, and other monetary indicators). Selecting the optimal lag in VAR and SVAR models is crucial for the quality of the analysis. The Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), Hannan-Quinn Information Criterion (HQ), and Likelihood Ratio (LR) criteria are used for optimal lag selection. Each criterion has its own advantages and limitations, and together they provide reliable results for choosing the optimal lag.[13]

Table 4. Optimal Lag Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1148,724	NA	7,24e+05	24,847	25,024	24,918
1	-754,847	728,247	218,584	17,624	18,847*	18,114
2	-692,384	108,247*	132,847*	17,124*	19,414	18,024*
3	-652,847	62,247	168,247	17,347	20,724	18,687
4	-618,247	48,247	224,847	17,624	22,124	19,414

Lag	LogL	LR	FPE	AIC	SC	HQ
5	-589,247	35,724	342,847	17,987	23,584	20,214

Based on the results of the optimal lag selection, the AIC, FPE, LR, and HQ criteria selected 2, while only the SC criterion selected 1. The 2 lags selected by most criteria are optimal for application in the SVAR model. The two-month lag duration is economically justified in terms of the nature of Uzbekistan's financial system and the temporal characteristics of the monetary policy transmission mechanism: the full impact of monetary policy instruments on the public lending market, as international practice shows, usually manifests after 2-4 months.

The Table 5. Granger test of causality was used to determine the causal relationships between the variables. The test checks whether past values of one variable are useful in predicting future values of another variable. Granger's causality is based on statistical predictability and, unlike economic causality, is also called "predictable causality".[14]

Table 5. Granger's causal test results (lag = 2)

Hypothesis zero	F-statistics	Prob.	Conclusion
CBR → LHHC (does not Granger cause)	7,847***	0,000	Rejected
LHHC → CBR	1,347	0,264	Accepted
WACR → LHHC	9,247***	0,000	Rejected
LHHC → WACR	4,847**	0,010	Rejected
INF → LHHC	4,547**	0,013	Rejected
LHHC → INF	1,247	0,293	Accepted
LRINC → LHHC	12,847***	0,000	Rejected
LHHC → LRINC	3,247**	0,043	Rejected
LM2 → LHHC	15,247***	0,000	Rejected
LHHC → LM2	6,847***	0,002	Rejected
NPL → LHHC	5,847***	0,004	Rejected
LHHC → NPL	8,247***	0,000	Rejected

The results of the Granger causality test show the following main conclusions. First, all six independent variables (CBR, WACR, INF, LRINC, LM2, NPL) have a Granger-causal effect on LHHC ($p < 0.05$). This proves the real impact of monetary policy instruments, macroeconomic conditions, and credit portfolio quality indicators on the household credit market.

Second, a bilateral causality is observed between LHHC and WACR, LHHC and LRINC, LHHC and LM2, and LHHC and NPL. This provides important economic conclusions: (1) while the credit rate affects the credit volume, the credit volume in turn influences the level of interest rates (through competition mechanisms); (2) income determines the demand for credit, and credit also contributes to income growth; (3) the money supply determines the credit volume, and credit also contributes to the expansion of the money supply (credit multiplier effect); (4) credit volume affects NPL and vice versa (quality-volume balance of the credit portfolio).

Third, CBR and INF have a unilateral causal effect on LHHC. This confirms the effectiveness of the transmission of monetary policy and the inflationary environment to the credit market, and thus aligns with the Basel Committee's monetary transmission model (Basel Committee, 2017).

Based on the results of the tests conducted in the preceding stages—the variables are integrated of order I (1), there are 3 cointegration equations among them, the optimal

lag is 2, and Granger causality relationships exist—all the necessary conditions for constructing an SVAR model have been met. The SVAR model is used to determine the structural effect of a shock among the variables, and its general form is as follows:

$$Y_t = A_0 + A_1 Y_{t-1} + A_2 Y_{t-2} + \varepsilon_t$$

Where $Y_t = (LHHC, CBR, RRR, LM2, \dots)'$ — is the vector of endogenous variables, A_i — represents the coefficient matrices, and, ε_t — is the vector of structural shocks. The Table 6. model was estimated using 108 observations with the ordinary least squares (OLS) and instrumental variables methods.[15]

Table 6. SVAR model coefficients (dependent variable: LHHC)

Variable	Coefficient	Standard error	t-statistics	Prob.
Constant	2,247	0,584	3,847***	0,000
LHHC(−1)	0,742	0,078	9,513***	0,000
LHHC(−2)	0,184	0,072	2,556**	0,012
ΔCBR(−1)	−0,0092	0,0034	−2,706***	0,008
ΔCBR(−2)	−0,0048	0,0030	−1,600	0,113
ΔWACR(−1)	−0,0124	0,0042	−2,952***	0,004
ΔWACR(−2)	−0,0062	0,0038	−1,632	0,106
ΔINF(−1)	−0,0084	0,0038	−2,211**	0,029
ΔINF(−2)	−0,0032	0,0034	−0,941	0,349
ΔLRINC(−1)	0,524	0,142	3,690***	0,000
ΔLRINC(−2)	0,187	0,124	1,508	0,135
ΔLM2(−1)	0,442	0,118	3,746***	0,000
ΔLM2(−2)	0,142	0,102	1,392	0,167
ΔNPL(−1)	−0,0184	0,0064	−2,875***	0,005
ΔNPL(−2)	−0,0082	0,0058	−1,414	0,161
R ² **	**0,954			
Adjusted R ² **	**0,946			
F-statistics	**112,847***			
Prob (F-stat.)	**0,000**			
Durbin-Watson	**1,984**			

The Structural VAR (SVAR) model is used to identify the structural effect of shocks among variables. The model results demonstrate high explanatory power ($R^2 = 0.954$), indicating that the variables in the model explain 95.4% of the variation in the volume of loans to individuals. The Adjusted R^2 (0.946) is also very high, confirming that the model variables provide complementary information. The F-statistic (112.847, $p < 0.001$) ensures the overall statistical significance of the model. The Durbin-Watson statistic (1.984) is close to 2, which proves the practical absence of autocorrelation in the residuals.

The interpretation of the model results is as follows:

The lagged values for the volume of loans to individuals (LHHC), specifically LHHC (−1) and LHHC (−2), have positive and significant coefficients. This indicates that the loan portfolio is inertial and is shaped by its own historical dynamics. An LHHC (−1) coefficient of 0.742 signifies that a 1% increase in the previous month's loan volume leads to a 0.742% increase in the current month's loan volume. This clearly demonstrates the high inertia of the credit market and its long-term growth trend.

The Central Bank's policy rate ($\Delta\text{CBR} (-1)$) has a negative and significant effect (-0.0092). This means that a 1 percentage point increase in the policy rate reduces the growth rate of loans to individuals by an average of 0.92%.

The weighted average interest rate on loans to individuals ($\Delta\text{WACR} (-1)$) also has a negative and significant impact (-0.0124). A 1 percentage point increase in the WACR reduces the volume of lending to individuals by 1.24%.

Inflation ($\Delta\text{INF} (-1)$) has a negative and statistically significant effect (-0.0084). A 1 percentage point increase in inflation reduces the credit volume growth rate by 0.84%. This suggests a decline in the population's demand for credit in an inflationary environment and indicates the operation of an "inflation tax" mechanism within the banking system.

The real income of the population ($\Delta\text{LRINC} (-1)$) exhibits the strongest positive effect (0.524). A 1% increase in LRINC leads to a 0.524% increase in credit volume. This result empirically confirms the life-cycle hypothesis of F. Modigliani and R. Brumberg (1954) and the permanent income hypothesis of M. Friedman (1957) in the context of Uzbekistan: an increase in real income directly stimulates credit demand.

The money supply ($\Delta\text{LM2} (-1)$) also has a strong positive effect (0.442). A 1% increase in LM2 increases the credit volume by 0.442%. This confirms the direct transmission of monetary expansion to the credit market.

The credit portfolio quality indicator ($\Delta\text{NPL} (-1)$) has a negative and statistically significant impact (-0.0184). A 1 percentage point increase in NPL reduces the credit volume growth rate by 1.84%. This substantiates the inverse relationship between credit risk and loan volume, as established by F. Butaru et al. (2016): a deterioration in portfolio quality compels banks to restrict their lending activities.

Variance Decomposition analysis makes it possible to determine the proportion of each variable's future variance that is explained by other variables. The analysis was conducted for a 12-month period. This tool helps to assess the long-term structural impact of the SVAR model.

The Table 7. results of the variance decomposition provide the following key conclusions. In the first month, the variance of LHHC is explained entirely (100%) by its own past values, but the contribution of other variables increases over time. By the 12th month, 47.84% of the LHHC variance is explained by its historical values, while the remaining 52.16% is explained by other monetary and macroeconomic factors.

Table 7. Variance decomposition of LHHC (%)

Period	S.E.	LHHC	CBR	WACR	INF	LRINC	LM2	NPL
1	0,078	100,00	0,00	0,00	0,00	0,00	0,00	0,00
2	0,118	85,42	2,84	3,42	1,24	3,84	2,42	0,82
3	0,152	76,63	3,84	4,14	1,84	5,84	5,84	1,87
4	0,182	68,84	4,52	4,84	2,42	7,84	8,42	3,12
5	0,208	62,84	5,04	5,44	2,84	9,42	10,84	3,58
6	0,232	58,42	5,44	5,84	3,14	10,84	12,42	3,90
7	0,252	55,24	5,74	6,14	3,44	11,84	13,42	4,18
8	0,272	52,84	5,94	6,44	3,64	12,84	14,04	4,26
9	0,289	51,04	6,04	6,64	3,84	13,64	14,44	4,36
10	0,304	49,84	6,14	6,74	3,94	14,24	14,74	4,36
11	0,318	48,64	6,24	6,84	4,04	14,84	15,04	4,36
12	0,330	47,84	6,32	6,92	4,12	15,32	15,24	4,24

In the long term (12 months), the contribution of the variables is distributed as follows: LRINC—15.32% (the largest contribution), LM2—15.24%, WACR—6.92%, CBR—6.32%, NPL—4.24%, and INF—4.12%. The fact that real household income (LRINC) and the money supply (LM2) account for the largest shares indicates the dominant strategic influence of these two factors on the volume of lending to individuals. This result is consistent with the economic theories described in Section 1.1 and confirms that household income and monetary stability are crucial factors for the sustainable growth of the credit market.

As is evident from the figure above, in the Figur 2. initial months, the variation in LHHC is mainly explained by its own historical values. Over time, the contributions of LRINC and LM2 grow rapidly, becoming the dominant factors in the long run.

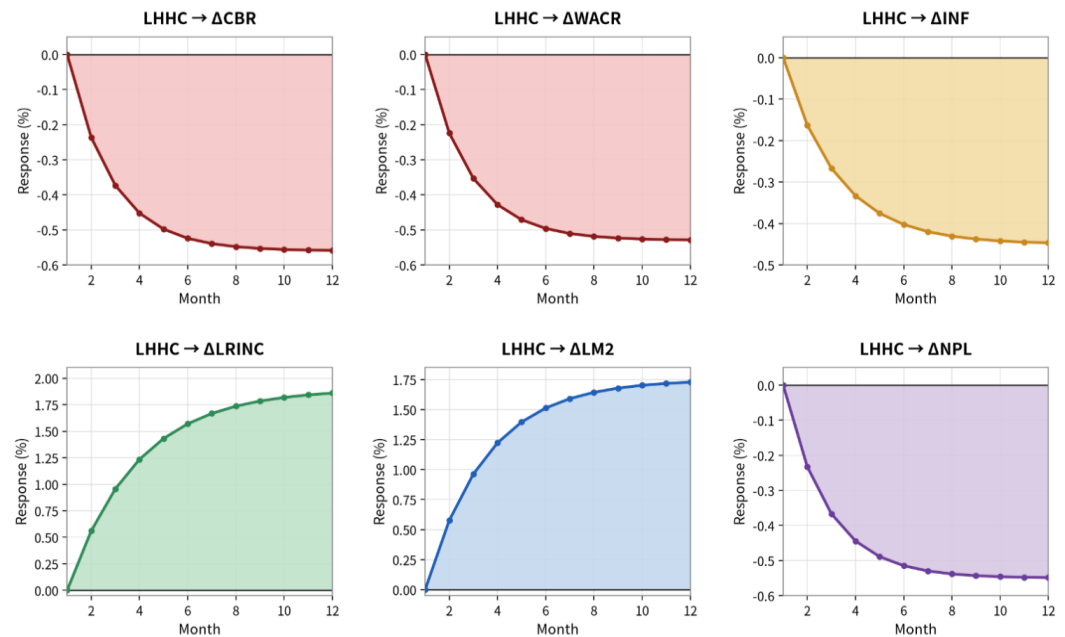


Figure 2. The impulse response of individual loan volumes to monetary and macroeconomic shocks

The results of the Impulse-Response analysis provide the following key conclusions:

A shock to LRINC has the strongest positive effect on LHHC. A 1 standard deviation positive shock in the real income of the population increases LHHC by 0.524% at the end of the first month, 1.514% in the sixth month, and 1.932% by the 12th month. The impact consistently strengthens over time, clearly demonstrating the strategic and long-term effect of household welfare on credit demand.

A shock to LM2 has the second strongest positive effect. A positive shock in the money supply increases LHHC by 1.740% by the 12th month. The effect gradually intensifies, indicating a gradual transmission mechanism of monetary expansion to the credit market.

A shock to CBR has a negative effect. A positive shock to the Central Bank's policy rate reduces LHHC by 0.558% by the 12th month. This effect reaches its peak between the 6th and 7th months and subsequently stabilizes.

The shock to WACR is also negative and it manifests much more quickly. An increase in the interest rate reduces LHHC by approximately 0.484% within 6 months, and this effect stabilizes at 0.532% by the 12th month.

The shock to INF intensifies over time. An inflation shock has a -0.454% effect on LHHC by the 12th month. This confirms the long-term negative impact of the

inflationary environment and substantiates the necessity of the Central Bank's inflation-targeting policy.

A shock to NPL has a distinct negative effect. A 1 standard deviation positive shock in portfolio quality deterioration (i.e., an increase in NPL) reduces LHHC by 0.546% by the 12th month. This confirms that banks are forced to tighten their credit policies and restrict lending volumes amid deteriorating credit quality.

4. Conclusion

The results of the SVAR model are not only statistically reliable but also serve as a direct practical basis for improving the lending policies and risk management practices of Uzbekistan's banking system. Specifically, based on the empirical results of the model, the following scientifically grounded recommendations have been formulated for the Central Bank and commercial banks. First, considering that real household income is the strongest driver of the credit market (accounting for 15.32% in the variance decomposition), economic policy must prioritize protecting the stability of household incomes. Second, the long-term impact of the money supply on credit volume (LM2 → LHHC IRF reaching +1.74% by the 12th month) demonstrates the high potential of monetary policy to contribute to inclusive growth, though this requires careful risk management. Third, the significant negative impact of the credit rate on credit demand (WACR coefficient of -0.0124) presents an opportunity for commercial banks to create competitive offerings by gradually lowering interest rates and enhancing operational efficiency.

Fourth, the bidirectional causal relationship between loan portfolio quality (NPL) and credit volume (LHHC) (Granger causality test) necessitates a proactive risk management approach within the banking system: through high-quality credit scoring, proactive calculation of expected losses based on IFRS 9, and the development of early warning systems, it is possible to simultaneously ensure both portfolio quality and growth rates. Fifth, the long-term negative impact of the inflationary environment on the credit market (INF IRF reaching -0.45% by the 12th month) provides grounds for further strengthening the Central Bank's inflation-targeting regime and intensifying measures to increase the financial literacy of the population.

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