An Integrated Stochastic Framework for Modeling Bank Financial Risks under Macroeconomic and Geopolitical Instability

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Abstract: For Ukrainian banks, the years 2021-2025 were marked not only by wartime shocks but also by changes in the way separate financial risks interacted. This article studies these interactions for the TOP-20 banks by regulatory capital, using official statistics of the National Bank of Ukraine. The proposed integrated risk indicator L_{tot} combines four risk contours: credit, market, liquidity and operational/buffer-related. Its construction is based on an economic logic rather than a purely technical aggregation. Credit risk is treated as the main loss-generating contour; foreign exchange-market and liquidity risks are interpreted as channels of shock transmission; and the operational/buffer-related component reflects the ability of a bank either to absorb or to amplify these shocks. The full MS-DCC-copula-Bayesian architecture is used as a conceptual framework, since the available Ukrainian data form a short panel and do not allow reliable direct estimation of the complete specification. The empirical validation therefore relies on a more transparent set of tools: VaR, Expected Shortfall, panel VAR(2), EWMA-based dependence estimates, FEVD, CUSUM diagnostics and stress simulation.The results show that the fall in integrated risk after the initial wartime shock should not be interpreted as the disappearance of vulnerabilities. In 2025, L_{tot} increased again, mainly because of renewed credit and portfolio risks. Expected Shortfall was highest in 2021-2022, while the combined stress scenario for 2025 produced the strongest tail-risk effect. The VAR and FEVD results are especially important for the logic of the model: at the third forecast horizon, liquidity shocks explain up to 20.27% of the variance of the credit-risk contour. This means that liquidity risk is not only a supporting indicator but also a channel through which credit vulnerability may develop. The findings suggest that a simple additive treatment of bank risks may understate their interaction under wartime and structural instability.

1 INTRODUCTION

Financial risks in banking are becoming harder to assess because they rarely develop in isolation. Credit, market, liquidity and operational risks are increasingly connected through balance sheets, funding channels, customer behaviour and market expectations. During periods of stress, a shock in one area may quickly affect other parts of the bank's risk profile.

This problem has become more visible in recent years. Global financial integration, digitalisation of banking services, financial technologies, the COVID-19 pandemic, geopolitical tensions and exchange-rate volatility have increased the speed and complexity of risk transmission. These factors also show that financial processes may become nonlinear and unstable, especially when the economic environment changes abruptly.

Banks now use many quantitative tools: probability-of-default models, Value-at-Risk, Expected Shortfall, volatility models, stress testing and economic capital approaches. However, these tools are often applied separately to individual risk categories. As a result, risk managers may receive several useful indicators but still lack a coherent view of the bank's total risk profile. This fragmentation can also affect managerial decisions on risk appetite, limits and capital allocation.

Classical econometric models have additional limitations. Assumptions of linearity, parameter stability and stationarity make models easier to estimate, but they do not always reflect how banks operate in practice. Structural breaks, regime shifts and rapid changes in the behaviour of borrowers, depositors and market participants may reduce the reliability of models based only on historical data.

The Ukrainian banking sector is a relevant case for this problem. In 2021-2025, banks operated under wartime uncertainty, exchange-rate pressure, changes in borrower quality and structural adjustment of the economy. In such conditions, different types of risk cannot be treated as fully independent.

The aim of this study is to develop and empirically validate an integrated stochastic framework for modeling bank financial risks. The proposed approach treats credit, market, liquidity and operational risks as interconnected contours and combines econometric modeling, dynamic dependence analysis and adaptive updating to obtain a more consistent representation of the banking risk profile.

2 REVIEW OF LITERATURE

The literature on bank financial risks did not emerge from a single research tradition. Its theoretical basis was gradually formed at the intersection of uncertainty theory, financial economics and portfolio theory. The early works of F. Knight, J. Keynes and A. Pigou were important because they drew attention to the difference between measurable risk and broader economic uncertainty. For banking research, this distinction remains essential: not every potential loss can be described only through historical frequencies or stable probability distributions.

Later, modern financial theory gave risk a more formal analytical interpretation. W. Sharpe and J. Tobin contributed to the development of portfolio thinking, where risk is assessed not only through individual assets but also through their interaction within a portfolio. M. Friedman, F. Modigliani and M. Miller strengthened the theoretical basis for analyzing financial decisions, capital structure and market behaviour. The works of R. Merton and M. Scholes further expanded quantitative finance by formalizing risk valuation and asset pricing under uncertainty.

These contributions created the foundation for many tools used in contemporary financial risk management. However, their direct application to banking risk assessment is not without limitations. Classical models often assume market efficiency, stable distributions, linear relationships and parameter stability. Such assumptions are useful for building clear analytical models, but they become less reliable when the financial environment is affected by structural instability, regime shifts and systemic shocks.

This limitation is important for the present study because the Ukrainian banking sector in 2021-2025 illustrates an environment in which credit, market, liquidity and operational risks cannot be interpreted as fully separate categories. In the proposed framework, this idea is reflected in the integrated indicator L_{tot}, where individual risks are treated as interacting contours rather than mechanically summed variables. Under wartime and macro-financial stress, these contours may transmit shocks through banks' balance sheets and amplify one another.

3 METHODOLOGY

The methodological logic of the study follows from a practical problem observed in bank risk management. Credit, foreign exchange-market, liquidity and operational risks are usually reported in separate blocks, although in periods of stress they rarely remain separate. A deterioration in loan quality may create additional liquidity pressure; exchange-rate movements may affect borrowers' repayment capacity and banks' open positions; operational or buffer-related constraints may strengthen the final impact of financial shocks. For this reason, the bank is considered here as a financial system in which risks interact through balance-sheet and market channels.

The theoretical basis of the methodology is drawn from financial risk theory, economic capital logic and enterprise risk management. These concepts are used not as a formal background, but as a way to justify the construction of the integrated risk indicator L_{tot}. In this indicator, the credit contour is treated as the main source of potential losses. The foreign exchange-market and liquidity contours are interpreted as channels through which shocks are transmitted or redistributed within the bank's balance sheet. The operational/buffer-related component reflects whether the bank has enough capacity to absorb pressure or, conversely, whether this pressure may be amplified.

A full MS-DCC-copula-Bayesian specification is useful as a conceptual architecture because it reflects volatility dynamics, changing dependence between risks, nonlinear aggregation and parameter updating.

In the present study, however, it is not estimated in its complete form. The reason is empirical rather than theoretical: the available Ukrainian banking data for 2021-2025 form a short panel, and direct estimation of the full structure would be unstable. Therefore, the empirical block is built as a reproducible approximation based on official statistics of the National Bank of Ukraine.

The first step is a descriptive analysis of the main risk contours and the integrated indicator. Correlation analysis is then used to check whether the contours move together and whether their relationships are strong enough to justify further dynamic testing. After that, a panel VAR(2) model is estimated for the credit, foreign exchange-market and liquidity contours. Bank fixed effects are removed in order to reduce the influence of differences between institutions. In this setting, the VAR model is not treated as a final structural model of the banking system. Its role is more specific: to test whether lagged shock-transmission channels between the risk contours can be observed in the available data.

For the dependence block, EWMA estimates are used instead of a full DCC-GARCH estimation. This choice is deliberate. With annual data and a short time dimension, EWMA provides a more cautious approximation of time-varying volatility and correlations. It allows the analysis to reflect changes in dependence between contours without overloading the data with an excessively complex specification.

Tail risk is assessed through Value-at-Risk and Expected Shortfall calculated from the cross-sectional distribution of L_{tot} across the sampled banks. These estimates are interpreted carefully. Since each year contains a limited number of observations, VaR and ES are used as proxy measures of tail-risk concentration rather than as exact parametric estimates of extreme losses.

The dynamic results are additionally checked through FEVD and CUSUM diagnostics. FEVD is used to show how shocks to one risk contour contribute to the variance of another. This is especially relevant for the relationship between liquidity and credit risk, because the results indicate whether liquidity is only a supporting indicator or a real transmission channel. CUSUM diagnostics are applied to check whether the estimated VAR relationships remain locally stable within the sample period. The final part of the methodology is a stress simulation, where separate and combined shocks are applied to evaluate how the integrated risk indicator changes under adverse conditions.

4 RESULTS

Risk measurement in banking has advanced through PD/LGD models, VaR and Expected Shortfall, volatility models, stress testing and economic capital methodologies. In practice, these tools are still often applied to separate risk categories with different data, horizons and assumptions. Risk managers receive many indicators but not always a coherent view of the bank's total risk profile. Model outputs are also not always linked to risk appetite, limits or capital allocation. BCBS 239 therefore emphasizes consistent risk data aggregation and reporting [1].

Data governance does not remove the problem of interaction between risks. Links between credit, market, liquidity and operational risks may change under stress. Correlations that appear stable in normal periods can strengthen, weaken or break down during turbulence, leading to underestimation of aggregate and tail risk [2]. This explains the use of copula-based and multifactor approaches for nonlinear dependence and joint extreme losses [3]. Macro-financial instability complicates aggregation, as shocks may spill over across markets and balance sheets [4], [5].

Technological change adds another layer. Digitalisation improves banking operations, but cyber resilience, operational continuity and dependence on third-party providers are now part of the risk profile. DORA and the EBA Guidelines stress integrated data governance, controls and reporting [6]-[8]. Regulators note that geopolitical and cyber risks may be poorly captured by models calibrated only on historical data [9]. Stress scenarios and forward-looking overlays should therefore be embedded in the model.

For Ukrainian banks, this is especially relevant because they operate under wartime uncertainty, exchange-rate volatility and structural adjustment. An integrated model must aggregate traditional risks and remain usable under structural breaks, changes in borrower quality and operational vulnerabilities. Figure 1 summarizes the logic of the proposed system. It shows how different sources of information - bank-level indicators, macroeconomic variables, wartime factors, behavioural signals and digital-risk indicators - can be linked with the modeling and management blocks [10], [11].

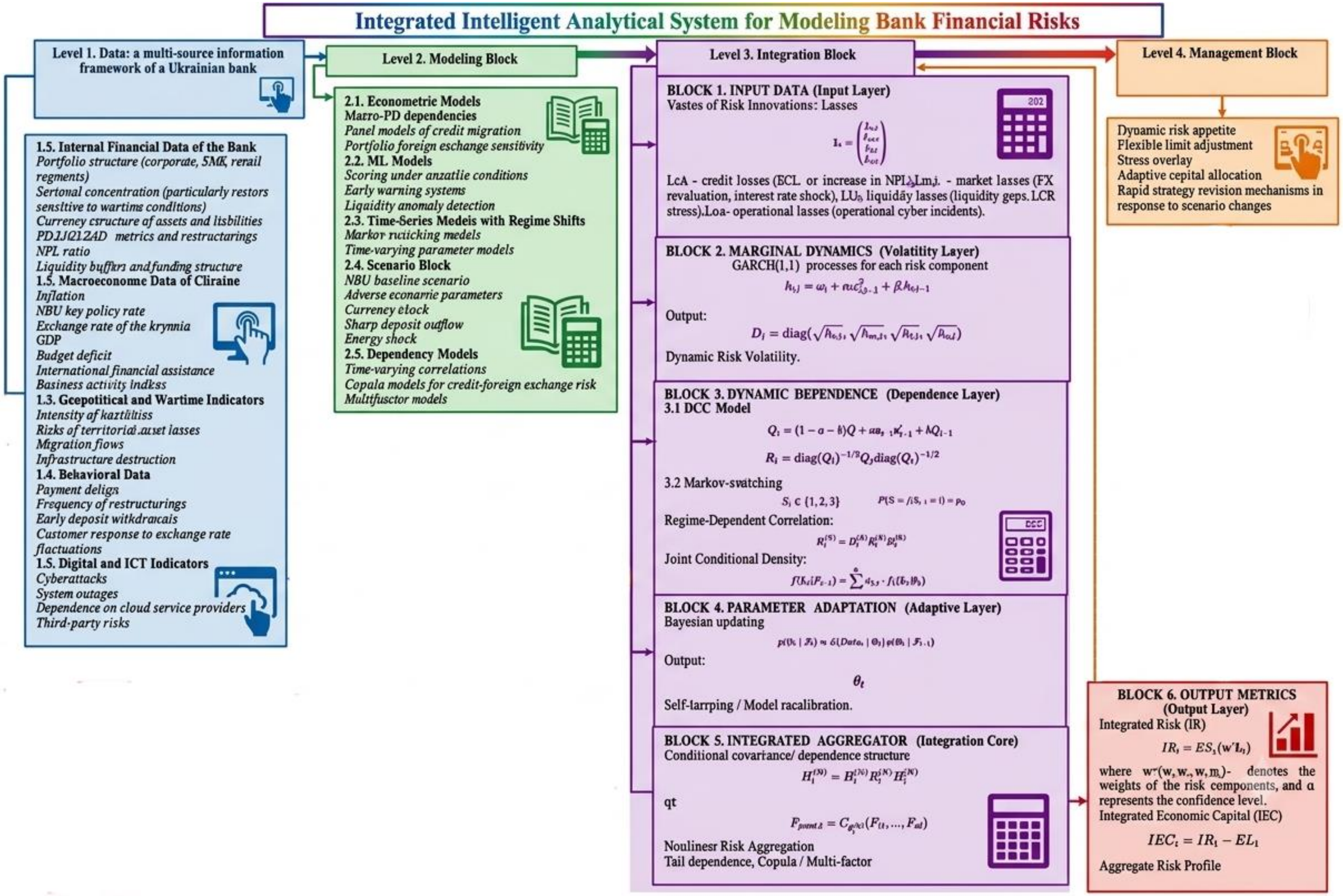

Figure 1: Architecture of the Integrated Intelligent Analytical System for Modeling Bank Financial Risks (Taking into Account the Specifics of Ukraine) Compiled by the authors.

The main role of this scheme is not to present a single mechanical algorithm, but to show how separate risk contours may be brought into one analytical structure.

The empirical part of the study is based on panel data for the TOP-20 Ukrainian banks over 2021-2025. The sample is formed using official statistics of the National Bank of Ukraine, which makes the calculations reproducible and allows the results to be compared across banks. The list of banks included in the sample is presented in Table 1.

The full MS-DCC-copula-Bayesian structure is used in this study as a conceptual model of integrated risk. It reflects the logic of marginal volatility, regime-dependent correlations, nonlinear aggregation and parameter updating. At the same time, the available Ukrainian data have a short time dimension.

For this reason, the empirical validation is carried out through a more cautious approximation: a panel dynamic model, EWMA-based dependence estimates and an aggregated stochastic block. This choice allows the study to preserve the idea of integrated risk modeling without overloading the data with a specification that cannot be estimated reliably under short-panel conditions.

Within the framework of the proposed methodology, the risk contours are constructed so that the integrated indicator reflects both the "core" of risk (the credit contour) and the transmission channels operating through the currency and liquidity mechanisms. To ensure a continuous time panel for 2021-2025, a unified measurement of the credit contour Lc was employed in the VAR block, defined as a normalized proxy based on the H7 ratio (min-max normalization within each year).

For risk profiling of 2025 and stress scenarios, the IFRS 9 credit indicator was applied, as it is substantively closer to portfolio quality and is necessary for drawing practical conclusions regarding the credit contour (Table 2).

The dynamics of the indicator are economically consistent. After 2022, the overall level of integrated risk in the banking system decreases, but in 2025 it rises again. This increase is mainly associated with the growth of the proxy credit-risk component L_c. This suggests that concentration and portfolio vulnerabilities may reappear even when liquidity conditions remain relatively stable.

Given that the integrated model focuses on risk under rare but high-impact loss scenarios, systemic risk is assessed using the Value-at-Risk (0.95) and Expected Shortfall (0.95) measures derived from the distribution of the integrated risk indicator L_{tot} across banks for each year (Table 3).

The results show that the Expected Shortfall at the 0.95 level was highest in 2021-2022, reaching approximately 0.71. This indicates that in the most adverse 5% of cases the level of integrated risk in the banking system was particularly elevated.

Table 1: List of banks included in the sample (2025, TOP-20 by N1 regulatory capital).

No.	Bank Code (NKB)	Bank Name	H1, thousand UAH
1	46	JSC CB "PrivatBank"	59941723
2	6	JSC "Oschadbank" (State Savings Bank of Ukraine)	26966981
3	296	JSC "OTP Bank"	18818365
4	36	JSC "Raiffeisen Bank"	18721832
5	115	JSC "PUMB" (First Ukrainian International Bank)	16997163
6	242	JSC "Universal Bank"	14219578
7	2	JSC "Ukreximbank" (State Export-Import Bank of Ukraine)	13230229
8	274	JSB "Ukrgasbank"	13016217
9	136	JSC "Ukrsibbank"	11907338
10	272	JSC "Sense Bank"	9408731
11	171	JSC "Credit Agricole Bank"	8323420
12	106	Joint-Stock Bank "Pivdennyi" (Bank Pivdennyi)	6410044
13	88	JSC "Kredobank"	5771134
14	295	JSC "ING Bank Ukraine"	4911949
15	298	JSC "ProCredit Bank"	4210975
16	96	JSC "A-Bank"	3639285
17	297	JSC "Citibank"	3219080
18	62	JSC "Tascombank"	3116695
19	305	PJSC "VST Bank"	2246545
20	153	JSC "Pravex Bank"	1562029

Table 2: Average values of the main risk contours and the integrated risk indicator for the banking system, 2021-2025.

Years	L_c (proxy)	L_m	L_l	L_o	L_{tot}
2021	0.505981	0.216158	0.442295	0.261637	0.404476
2022	0.357896	0.253646	0.487897	0.277303	0.367987
2023	0.367887	0.018209	0.364989	0.271259	0.287419
2024	0.177925	0.013176	0.327349	0.268264	0.198837
2025	0.458580	0.072060	0.325629	0.255184	0.321051

In contrast, ES declined in 2023-2024, suggesting a period of relative stabilization. However, in 2025 the indicator increased again to 0.5926. This supports the use of a dynamic risk management framework: even when several aggregate metrics improve, the system may still accumulate latent vulnerabilities.

Table 3: Estimates of tail systemic risk based on the integrated risk indicator, 2021-2025.

Year	VaR 0.95	ES 0.95
2021	0.614961	0.708452
2022	0.582274	0.710629
2023	0.538932	0.608442
2024	0.315917	0.535014
2025	0.450421	0.592557

The estimation of VaR(0.95) and Expected Shortfall within each year is performed on the cross-sectional distribution of the integrated indicator L_{tot} for the sample of the TOP-20 banks. Given the limited number of observations per year (n=20), the empirical estimation of the 95% quantile is based on a narrow tail segment of the distribution.

Accordingly, the obtained values should be interpreted as proxy estimates of tail risk, reflecting the relative concentration of risks within the system rather than precise parametric estimates of extreme losses.

To enhance the robustness of the results, annual data pooling and consistency checks of indicator dynamics over time were applied. Further research may extend tail-risk estimation through a parametric t-distribution specification or bootstrap procedures.

Subsequently, the integrated model was verified through the estimation of a second-order panel VAR (PVAR(2)) based on the variables (L_c,L_m,L_l), with bank fixed effects eliminated using the within transformation. This point is especially relevant for the integrated framework. Instead of viewing risk contours as independent indicators, they should be interpreted as interconnected channels of shock transmission. The VAR framework makes it possible to test empirically whether such relationships exist within the system.

The estimation was conducted on 60 observations (20 banks × 3 years with two available lags). Tables 4-6 present the regression results, including coefficients, standard errors, t-statistics, and p-values (standard errors are cluster-robust at the bank level, which is appropriate for panel dependence within banks).

The dynamic panel VAR(2) model was estimated using the within transformation to eliminate bank fixed effects. Given the limited time dimension of the panel (2021-2025), the estimates may contain a certain degree of bias typical of dynamic panel models with lagged dependent variables (Nickell bias).

Therefore, the PVAR results are interpreted as a verification mechanism for analyzing shock transmission channels between risk contours rather than as a final structural estimation of system parameters.

In future research, it would be appropriate to apply GMM estimation (Arellano-Bond or system-GMM), including instrument validity testing (Hansen test) and second-order autocorrelation diagnostics, in order to minimize potential estimation bias under short-panel conditions.

Table 4: VAR(2) estimation results for the credit-risk contour L_c.

Regressor	coef	std.err	T	P
L_c(t−1)	−0.370791	0.112684	−3.290540	0.003846
L_m(t−1)	−0.069650	0.068170	−1.021710	0.319752
L_l(t−1)	0.730137	0.308814	2.364322	0.028864
L_c(t−2)	−0.123158	0.110305	−1.116516	0.278123
L_m(t−2)	−0.034885	0.071723	−0.486382	0.632259
L_l(t−2)	−1.011657	0.360357	−2.807374	0.011242

Table 5: VAR(2) estimation results for the foreign exchange-market risk contour (L_m).

Regressor	Coef	std.err	T	P
L_c(t−1)	0.075536	0.023557	3.206882	0.004610
L_m(t−1)	0.007000	0.036482	0.191930	0.849958
L_l(t−1)	−0.175032	0.060211	−2.906304	0.009179
L_c(t−2)	0.006586	0.022263	0.295781	0.770627
L_m(t−2)	−0.261948	0.056635	−4.626219	0.000159
L_l(t−2)	0.005118	0.062215	0.082262	0.935249

Table 6: VAR(2) estimation results for the liquidity-risk contour L_l.

Regressor	Coef	std.err	T	P
L_c(t−1)	−0.023140	0.065213	−0.354835	0.726591
L_m(t−1)	−0.038060	0.017954	−2.120094	0.047181
L_l(t−1)	0.350988	0.111455	3.148838	0.005418
L_c(t−2)	0.051644	0.058836	0.877632	0.391432
L_m(t−2)	0.014211	0.017704	0.802685	0.432002
L_l(t−2)	−0.152851	0.116620	−1.310711	0.205523

Table 7: Granger causality results for risk-contour interactions in the VAR(2) model, F(2,19).

Equation (dependent variable)	Cause	F-stat	p-value
L_c	$L_m \Rightarrow L_c$	2.6470	0.0968
L_c	$L_l \Rightarrow L_c$	4.2056	0.0307
L_m	$L_c \Rightarrow L_m$	3.0100	0.0732
L_m	$L_l \Rightarrow L_m$	0.9563	0.4020
L_l	$L_c \Rightarrow L_l$	0.7232	0.4981
L_l	$L_m \Rightarrow L_l$	1.1176	0.3476

The economic interpretation of this equation is particularly important within the framework of the integrated model: the credit contour responds to the liquidity contour with lags, and the signs indicate a nonlinear (redistributive) nature of interaction within a short panel. Specifically, an increase in L_l (liquidity risk, measured as the inverse of LCR) in the first lag is associated with an increase in credit risk, whereas in the second lag it is linked to a compensatory effect (reverse movement).

The results indicate that within the integrated framework the foreign exchange-market risk contour acts not only as a potential source of shocks but also responds to changes in credit and liquidity conditions. The statistical significance of $L_c(t-1)$ indicates that an increase in credit risk reinforces foreign exchange constraints/positions in the subsequent period (the channel "portfolio quality → FX constraints/position").

At the same time, $L_l(t-1)$ exhibits a negative effect: during phases of liquidity stress, banks tend to reduce their foreign currency activity and risk exposure.

The high significance of $L_m(t-2)$ with a negative sign reflects an adjustment of the foreign exchange position at the second-lag horizon, indicating a delayed corrective mechanism in response to prior imbalances.

The liquidity contour exhibits the highest degree of inertia in the first lag (with Ll(t−1) statistically significant), while the effect of the foreign exchange contour Lm(t−1) is statistically significant and negative. This indicates that foreign exchange constraints/positions in the previous period are associated with a deterioration of the liquidity position in the subsequent period - a typical transmission channel of "FX stress → liquidity."

This result matters for the interpretation of L_{tot}. Liquidity risk is not only a supporting element of the integrated indicator. The estimates show that changes in liquidity conditions may affect other parts of the bank's risk profile, especially the credit contour. Therefore, L_l should be interpreted not only as a measure of the current liquidity position, but also as a possible channel through which shocks move inside the system.

Panel Granger causality tests were then used to check this relationship more formally. The purpose was to see whether lagged values of one risk contour help explain changes in another contour within the VAR(2) model. The joint significance of the lagged variables was tested using an F-test with df=(2,19). The results are presented in Table 7.

The Granger causality results give an important additional argument for the integrated interpretation of risk. At the 5% significance level, liquidity risk has a statistically significant Granger-type effect on credit risk ($L_l \Rightarrow L_c$, p=0.0307). In practical terms, this means that past changes in the liquidity contour help explain later movements in the credit contour. This result is economically plausible: when liquidity conditions deteriorate, banks may face tighter balance-sheet constraints, higher funding pressure and weaker room for credit portfolio adjustment. These pressures can later be reflected in credit-risk dynamics.

The relationship between the foreign exchange-market contour and credit risk is weaker, but it should not be ignored. For $L_m \Rightarrow L_c$ the null hypothesis is rejected at the 10% significance level (p=0.0968). This result should be read cautiously. It does not suggest that exchange-rate or market shocks immediately produce credit losses. More likely, their effect appears with a delay or is transmitted through intermediate channels, especially liquidity and balance-sheet adjustment. This interpretation is more consistent with the short-panel structure of the data and with the logic of banking risk transmission.

These results support the main idea of the integrated model: risk contours do not operate independently. Some effects are direct, while others become visible only after shocks pass through the balance sheet or accumulate in the tail of the loss distribution. This is why Expected Shortfall is used together with VAR-based diagnostics. It helps capture not only average interactions between risks, but also the behaviour of the system under adverse conditions.

To examine this structure in more detail, Forecast Error Variance Decomposition was calculated on the basis of the estimated VAR(2) model. The Cholesky ordering (L_c, L_m, L_l) was used, and the results were reported for one-, two- and three-period horizons. FEVD makes it possible to see how much of each risk contour's variation is explained by its own shocks and how much is transmitted from other contours. In this study, this step is especially useful because it shows whether liquidity and market shocks only accompany credit risk or actually contribute to its dynamics over time. The results are presented in Tables 8-10. The FEVD results add an important point to the interpretation of the integrated model. At the second and third forecast horizons, the role of liquidity shocks in explaining the credit contour becomes more visible, reaching 20.27% at horizon 3. This suggests that credit risk is not purely idiosyncratic or limited to the quality of individual loan portfolios. Part of its dynamics is shaped by liquidity conditions, which means that liquidity pressure may gradually turn into credit vulnerability within the banking system.

Table 8: FEVD, Horizon 1 (%, VAR(2)).

Variable	Shock L_c	Shock L_m	Shock L_l
L_c	100.00	0.00	0.00
L_m	2.14	97.86	0.00
L_l	3.16	1.19	95.65

Table 9: FEVD, Horizon 2 (%, VAR(2)).

Variable	Shock L_c	Shock L_m	Shock L_l
L_c	91.93	0.01	8.06
L_m	4.42	92.09	3.49
L_l	2.85	1.06	96.09

Table 10: FEVD, Horizon 3 (%, VAR(2)).

Variable	Shock L_c	Shock L_m	Shock L_l
L_c	79.45	0.28	20.27
L_m	4.16	92.55	3.29
L_l	3.81	1.05	95.14

At the same time, the foreign exchange contour remains largely self-determined (over 92% at horizons 2-3), suggesting an important practical implication for the integrated system: foreign exchange-market risk requires separate limit-setting and monitoring as a "primary regime factor," whereas the credit contour more strongly reflects interaction with liquidity and balance-sheet conditions.

To ensure the validity of applying VAR relationships in risk management (forecasting and stress assessment), the CUSUM test (cumulative sum of recursive residuals) was conducted for each VAR(2) equation. The test was implemented using recursive estimation with skip = 25 (to ensure a non-singular initial regressor matrix), at a 95% confidence level. Parameter instability is inferred if the CUSUM statistic crosses the corresponding confidence bounds (Table 11).

Table 11: CUSUM Test Results (95% Confidence Bounds).

Equation (risk contour)	Recursive observations	Max CUSUM	Boundary crossing: No
L_c (credit risk)	35	0.3840	No
L_m (market risk)	35	0.1732	No
L_l (liquidity risk)	35	0.1130	No

The results of the CUSUM test indicate that the estimated VAR(2) specification remains stable within the sample period. In other words, the transmission relationships identified between the different risk contours are unlikely to be the result of random fluctuations in the data.

Diagnostic tests confirm the absence of critical parameter breaks within the estimation interval; however, these findings should be regarded as evidence of local stability rather than proof of structural invariance of the model in the long run.

Methodologically, it is also emphasized that dependencies between contours evolve over time. With annual data, full MLE estimation of a classical DCC-GARCH model is statistically inappropriate due to the short time dimension T. Therefore, for a proper approximation, EWMA-based estimates of conditional variances and covariances were applied (a DCC-type approach for low-frequency series of system averages) (Tables 12-13).

Table 12: EWMA Volatilities of Risk Contours (λ = 0.94, system averages).

Year	σ_L_c	$\sigma\ L_m$	$\sigma\ L_l$
2021	0.112529	0.101030	0.064826
2022	0.113814	0.101059	0.064162
2023	0.110415	0.103727	0.066701
2024	0.107060	0.103305	0.064950
2025	0.114336	0.103196	0.064793

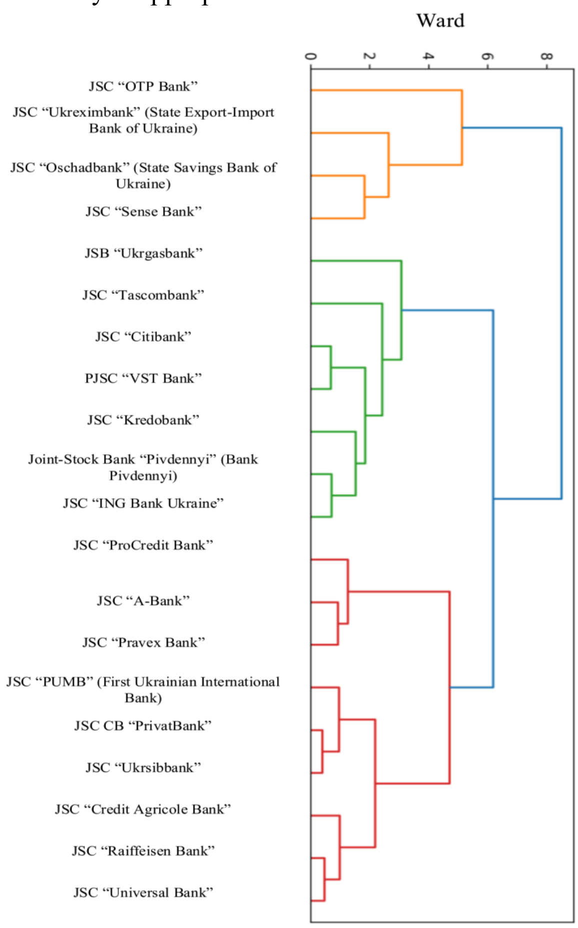

Figure 2: Dendrogram of bank clustering by risk profile (2025).

Table 13: DCC-type (EWMA) Correlations Between Risk Contours (System Averages).

Year	$\rho(L_c,L_m)$	$\rho(L_c,L_l)$	$\rho(L_m,L_l)$
2021	0.493318	0.337703	0.929144
2022	0.521800	0.367383	0.931169
2023	0.488362	0.336507	0.937453
2024	0.480042	0.336283	0.931159
2025	0.517176	0.385955	0.934421

The high and stable correlation $\rho(L_m,L_l)$=0.93-0.94 is consistent with the VAR results regarding shock transmission and confirms the systemic nature of the interaction between the foreign exchange and liquidity contours within the integrated risk management framework.

For the practical interpretation of the integrated model at the micro level, a clustering of banks by risk profile in 2025 was performed using the vector (L_c IFRS9, L_m, L_l, L_o, L_{tot}) (Fig. 2).

The clustering results are useful from a practical point of view. They show that banks differ not only by one risk indicator, but by a combination of several characteristics: credit quality measured through Stage 3 exposures, foreign exchange position (H12), liquidity pressure measured through the inverse of LCR, and the operational/buffer-related component (L_o). This makes the clustering more informative for supervision and internal risk management. It allows banks to be viewed as groups with similar risk profiles rather than as institutions to which the same supervisory response should automatically be applied.

This distinction is important because two banks may have a similar level of total risk but a different internal structure of that risk. One bank may be more exposed to credit-quality problems, while another may be more sensitive to liquidity or foreign exchange pressure. For this reason, the results of clustering can support a more targeted approach to supervisory monitoring, limit-setting and capital planning.

A separate stress simulation was also carried out for 2025. For this stage, the credit contour was measured using the IFRS 9-based indicator L_c, since it better reflects the quality of the loan portfolio. Four individual shock scenarios were considered, together with one combined scenario. In each case, VaR(0.95) and Expected Shortfall(0.95) were recalculated using the cross-sectional distribution of the integrated risk indicator L_{tot} across the sampled banks. The results are presented in Table 14.

Table 14: Integrated risk estimates under 2025 stress scenarios: VaR and Expected Shortfall.

Scenario	VaR 0.95	ES 0.95
Base (2025, IFRS9)	0.260617	0.276822
FX shock: Lm×1.20	0.288041	0.294340
Credit shock: Lc×1.30	0.294188	0.312126
Liquidity shock: LCR−25% (Ll×1.333)	0.298480	0.300671
Combined (1)-(3)	0.328876	0.353494

The stress results are quite clear: the combined scenario generates the highest tail-risk level in 2025, with Expected Shortfall reaching 0.3535. If the shocks are considered separately, the credit shock has the strongest effect. Its ES value rises to 0.3121, which confirms the central role of the credit contour in the integrated risk indicator. This is fully consistent with the weighting structure of the integrated indicator: the credit contour carries the largest weight; however, a liquidity shock rapidly amplifies the integrated loss due to the substantial share of L_l in the aggregation mechanism. Therefore, in a practical risk management framework, these contours should be monitored synchronously.

5 CONCLUSIONS

The results confirm that the proposed integrated system should be interpreted not only as a composite indicator, but also as an empirically tested model of interconnected risk contours. The VaR and Expected Shortfall estimates show the phase dynamics of tail systemic risk in 2021-2025. In particular, the renewed increase of the integrated indicator in 2025 points to the re-emergence of vulnerabilities after the period of relative stabilization.

The VAR(2) model estimated on panel data with within transformation identifies lagged interactions between the main risk contours. The results are especially important for the link between the foreign exchange-market contour, liquidity conditions and the credit profile of banks. FEVD additionally confirms that liquidity shocks increasingly contribute to the variance of the credit contour at the two- and three-period horizons. This supports the main assumption of the study: bank risks should not be treated as isolated exposures, since shocks may move through balance-sheet channels and affect other parts of the risk profile.

The CUSUM test indicates local stability of the estimated VAR structure within the sample. At the same time, the results should be interpreted with caution because the empirical analysis is based on a short panel of Ukrainian banks for 2021-2025. For this reason, the full MS-DCC-copula specification is treated as a conceptual model of integrated risk, while the applied estimation is used as an econometrically grounded approximation.

Despite these limitations, the analysis is based on official National Bank of Ukraine data, panel structure and robust standard errors. This provides a reliable basis for assessing the aggregate risk profile of the banking system under macro-financial volatility and geopolitical uncertainty. The proposed framework offers a more consistent way to evaluate how different sources of bank risk interact and how their joint effect may influence financial stability.

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