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Research Article

Credit Risk Shocks and Bank Resilience in Pakistan: Evidence from Dynamic Z-Score and NPL Interactions

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Abstract

The present study investigated the effect of credit risk management on the financial performance of commercial banks in Pakistan by utilizing quarterly data for eighteen listed commercial banks representing 80% of total banking assets during 2010-2022. This research employed Altman Z-score and dynamic panel regression as well as Vector Autoregression (VAR) models to identify the effects of credit risk (Gross Non-Performing Loan Ratio) on bank stability and performance. IRF analysis indicated that a one standard deviation shock to the GNPLR caused an approximate 0.23 decrease in Z-scores within eight quarters, with a peak impact in the second quarter. FEVD analysis determined that variation in the Z-scores accounted for between 12 and 15 percent of the variation in the Z-scores for a two-year forecast horizon. In panel regression results, prudent credit risk management reflected by non-performing loan ratios significantly impacts higher Z-scores, higher ROA, and higher equity to asset ratios. Also, macroeconomic factors such as GDP growth, inflation, and treasury bill rates significantly moderate the impact of credit risk shocks. The study will add to the nascent body of research on banking sector resilience in developing economies and provide pragmatic policy recommendations for banking regulators and commercial banks' management.
Keywords: Credit Risk, Bank Stability, Bank Performance, Non-Performing Loans, Z-Score, Emerging Markets, Pakistan.

Introduction

The commercial banks function as financial intermediaries in the developing countries, channeling the dormant resources in the economy into investment, which contributes to the growth of the economy (Berger & DeYoung, 1997). The commercial banking sector in Pakistan has witnessed tremendous changes over the past two decades, due to two crucial factors: the implementation of strict regulatory reforms and the introduction of the Basel III capital requirements and a rapid move towards the electronic banking system.

Even in such environments, the management of the credit risk, the probability of loan default by the borrower, is of utmost importance, especially in the context of trade finance (Ali & Ahmed, 2024). The level of the credit risk depends on the economic environment, as when unemployment levels are high during periods of recession, the income of households as well as companies decreases, leading to an increase in the loan default rate (Beyhaghi & Ehsani, 2017). The global financial crisis of 2008-2009, followed by the European debt crisis, highlighted the risks of poor credit risk management (Blinder, 2015). Decline in the quality of assets is a cause of a major systemic crisis. The problem is, however, that understanding the relationship between credit risk and the banks' balance sheet is a complex issue, particularly in emerging countries that are intrinsically linked to different macro-economic conditions and institutions (Haider & Hasan, 2015).

Motivation and contribution to research

This research makes four new contributions to the banking literature:

Comprehensive time series analysis: Unlike many previous studies based on annual data, it is possible to use quarterly observations over fifty-two periods to capture dynamic corrections and cyclical patterns that inevitably obscure annual data.

VAR Methodology: Apply vector autoregressive models using impulse response functions and predictive error variance distributions to monitor the dynamic effects of credit risk shocks in a system of broadly defined variables.

Panel and Time Series Integration: Leverage cross-sectional and temporal variability of data by combining panel regression with persistence and VAR analysis, providing complementary insights into the relationship between credit risk and stability.

Policy-Related Analysis: Identify counter-cyclical patterns and macroeconomic amplifying effects that directly impact bank supervisors and auditors.

Research Questions

This study answers the following questions:

1. What are the dynamic effects of credit risk shocks on the stability of banks, and at what horizon do they disappear?
2. How important is credit risk compared to other factors explaining differences in banking stability?
3. Does the impact of credit risk on banks' performance in economic cycles change systematically?
4. What is the appropriate policy response to the accumulation of credit risk in the Pakistani banking context?

Literature Review

Credit Risk in Banking: Theoretical Framework

Credit risk is considered a crucial factor in the loan process. When a bank approves credit, it acknowledges that the borrower may not be able to repay the principal or interest in full on time. Banks mitigate this risk through various diversification strategies, including collateral requirements, full credit analysis, and risk-based pricing. However, in times of systemic stress, traditional methods often fail because they are associated with bankruptcy and reduce secondary factors (Altman & Hotchkiss, 2010).

In this regard, Jensen and Meckling (1976) share a standardized approach to institutional credit risk theory. This approach invites claimants to take on excessive credit risk for potential profits after receiving the loan, forcing lenders to incur losses due to estate issues. A similar problem arises at the banking level, where limited liability systems encourage shareholders to transfer risk. Therefore, a robust credit risk management system, including surveillance, contractual agreements, and early warning indicators, is designed to mitigate these conflicts of interest between institutions (Reitan & Aas, 2010).

From a regulatory perspective, the Basel Agreement represents an international agreement on credit risk management. Basel I (1988) introduced standard capital requirements for credit exposure; Basel II (2004) built on this trend with innovative methods based on internal ratings; and Basel III (2010/2015) strengthened capital buffers and introduced liquidity requirements in response to the failure of the 2008 crisis (Basel Committee on Banking Supervision, 2017). In Pakistan, the central bank (State Bank of Pakistan) has phased in the Basel III directive, making effective credit risk management a key pillar of sound regulation (Iqbal et al., 2023).

Non-Performing Loans and Bank Performance

In the empirical literature, a consistently negative correlation between the non-performing loan ratio and bank profitability has been recorded. Salas and Saurina (2002) studied commercial banks in Spain and found that during boom periods, increased reserves are an important buffer during economic downturns, reducing overall profitability throughout the cycle. Louzis et al. (2012) examined Greek banks during a sovereign debt crisis and showed that the growth of non-performing loans is driven by a combination of bank-specific factors such as credit quality and asset quality management, as well as macroeconomic conditions such as GDP growth, unemployment rates, and interest rates.

In South Asia and equivalent developing countries, Kemraj and Pasha (2010) analyzed commercial banks in the Caribbean and concluded that NPL ratios are highly dependent on real interest rates and GDP growth, especially on real interest rates and GDP growth, and mainly on macroeconomic variables regarding NPL. Haider and Hasan (2015) analyzed Pakistani banks based on monitoring data from state-owned banks and noted that between 2010 and 2015, Pakistan's non-performing loan ratio was well above the regional average, averaging 8%.

The mechanism by which an increase in bad debt negatively affects the performance of banks is well known. Reduced interest income from unaccrued loans, rising reserves that reduce net income, opportunity costs of capital immersed in debt collection activities, regulatory capital ceilings that limit the development of the balance sheet, and reputational damage that increases financing costs (Afzal & Mirza, 2012).

Altman's Z-score methodology

Altman (1968) developed the original Z-score model to predict corporate bankruptcy using multi-discriminatory analysis. The model combines five financial indicators, each of which is weighted according to its discriminatory power:

$$Z = 1.2X^1 + 1.4X^2 + 3.3X^3 + 0.6X^4 + 1.0X^5 \quad (1)$$

where: X^1 = working capital / total assets; X^2 = Retained earnings / Total assets; X^3 = EBIT / Total Assets; X^4 = market value of equity/book value of liabilities; X^5 = Sales/Total Assets.

The result obtained is interpreted as follows: with > 2.99 means safe zone (low risk of danger); 1.81 < Out of < 2.99 indicates a gray area (medium risk); Z < 1.81 indicates a breakout zone (high risk of financial collapse). Altman et al. (2017) modified the model for financial institutions, replacing market values with book values where market data is not available. In banking applications, the Z-score has been adjusted to consider capital adequacy ratios, return on assets, and asset quality indicators specific to banking business models.

Empirical evidence for Z-score and bank stability

Gropp et al. (2006) apply an approach to insolvency—closely related to the Z-score framework—to 100 EU banks between 1992 and 2000, showing that capital ratios, profitability, and credit quality significantly affect the stability of banks. Hafeez et al. (2022) Apply the Altman Z-score to Pakistani commercial banks and conclude that banks with higher performance exhibit higher profitability and lower risk, confirming the Z-score as a multidimensional indicator of stability.

Studies that apply Z-score or equivalent stability indicators to Pakistani banks remain rare. This study fills this gap by applying Z-score analysis to a comprehensive panel of Pakistani banks with thirteen years of quarterly data.

Macroeconomic Factors of Credit Risk

Nkusu (2011) provides a comprehensive nationwide overview of how macroeconomic conditions shape the NPL ratio. Real GDP growth reduces precarious loans, as rising incomes strengthen borrowers' ability to repay; Inflation has mixed effects; and rising real interest rates raise the cost of repaying debt, which increases the likelihood of default.

Pakistan's macroeconomic environment between 2010 and 2022 was characterized by significant volatility, including the effects of the 2008 global crisis, several IMF support programs, the severe energy crisis (2010-2015), terrorism-related economic shocks, the COVID-19 pandemic (2020-2021), and the rise in inflation in 2022. This volatility provides a rich empirical context on how macroeconomic shocks enter the banking sector through credit risk channels (Ain et al., 2025).

Conceptual framework

Based on the above assessment, we model the impact of credit risk indicators determined by macroeconomic conditions and the uniqueness of banks. Macroeconomic variables - GDP growth, inflation, interest rates, and oil prices primarily affect credit risk and borrowers' ability to borrow. Credit risk indicators, especially the total national return of the economy, affect bank performance and stability and are measured by Z-scores, return on equity, capital adequacy, and operational efficiency. Bank-specific factors (management quality, risk culture, credit quality) and regulatory factors (capital requirements, intensity of oversight) undermine these relationships throughout the process.

Data analysis and Description

Data Sources and Sampling

The dataset includes quarterly observational data from eighteen commercial banks listed in Pakistan from Q1 2010 to Q4 2022, spanning a total of fifty-two quarterly periods. The banking model collectively accounts for about 80% of the total assets of the banking sector and offers a wide representation.

The participating banks are: Allied Bank Limited, Askari Bank, Bank Al-Falah, Bank Alhabib, Bank Islami Pakistan, Bank of Khyber, Bank of Punjab, Faysal Bank, Habib Bank Limited, Habib Metropolitan Bank, JS Bank, MCB Bank, Meezan Bank, National Bank of Pakistan, Standard Chartered Bank Pakistan, Soneri Bank, Summit Bank, and United Bank Limited.

Definition of Variable

Dependent Variable:

Z-score: The overall indicator of financial stability is structured as follows:

$$Z_{i,t} = (CAR_{i,t}/100) + (ROA_{i,t}/\sigma^8 ROA_{i,t}) + (EBIT_{i,t}/TA_{i,t}) \quad (2)$$

where there are eight quarters of the moving standard deviation ROA. σ^8

Return on Assets (ROA): Net income divided by total assets, expressed as a percentage.

Equity-to-asset ratio: total capital divided by total assets.

Key Independent Variable

GNPLR: Gross NPLs divided by gross loans, expressed as a percentage. It is the main measure of credit risk.

CAR: Capital adequacy ratio expressed as a percentage.

Macroeconomic controls: real GDP growth (%), CPI inflation (%), Treasury bill rate (%), and oil price (US dollar/barrel).

Summary statistics

Table 1. Descriptive Statistics - Full Sample, Q1 2010 - Q4 2022.

Variable	Mean	Std Dev	Minimum	Maximum	Median
Z-Score	2.689	2.156	−4 663	9.352	2.498
GNPLR (%)	7.345	8.921	−0 987	35.214	5.142
CAR (%)	16.85	4.023	7.891	32.106	16.140
LENGTH (%)	0.762	1.045	−3 288	4.986	0.801
GDP growth (%)	3.587	2.143	0.547	5.421	3.842
Inflation (%)	7.623	4.156	2.108	25.405	6.892

Table 1 shows the descriptive statistics of the variables of the study from Q1 2010 to Q4 2022. It shows that the banking system is robust as measured by its average capital adequacy ratio of 16.85%, but volatile as measured by a maximum Gross Non-Performing Loans Ratio (GNPLR) of 35.214%. The mean Z-score of 2.689, coupled with the high variance in inflation, where a maximum of 25.405% is registered, suggests that the solvency of banks has been evaluated.

Correlation analysis

Table 2. Correlation matrix (* indicates significance at the level of 5%).

Variable	Z-Score	GNPLR	CAR	ROA	GDP
Z-Score	1.000				
GNPLR	−0.471*	1.000			
CAR	0.342*	−0.711*	1.000		
ROA	0.670*	−0.563*	0.620*	1.000	
GDP	0.014	−0.011	−0.012	0.040	1.000

The correlation matrix in Table 2 reveals a strong negative relationship between the GNPLR and both the Z-score (r = −0.471) and CAR (r = −0.711), confirming that credit risk deterioration is strongly associated with reduced financial stability and capital adequacy. ROA correlates most strongly with the Z-score (r = 0.670), which emphasizes the importance of profitability as a driver of stability.

Research Methodology

Static Fixed Effects Mode

The basic model is as follows:

$$Z_{i,t} = \alpha_i + \beta^1 GNPLR_{i,t} + \beta^2 CAR_{i,t} + \beta^3 ROA_{i,t}{}^{-1} + \beta^4 Macro_t + u_{i,t} \tag{3}$$

Where i indexes banks (i = 1, ..., 18), t indexes quarters (t = 1, ..., 52), and α_i represents bank fixed effects that absorb all time-invariant, bank-specific characteristics. Fixed effects are preferred over random effects based on the Hausman (1978) test ($\chi^2 = 23.45$, $p < 0.01$). The F-test for joint significance of the bank fixed effects yields F (17,900) = 12.34, significant at the 1 percent level.

Dynamic Panel Specifications

Having the observed stability due to Z (the first row of the autocorrelation coefficient 0.42), we supplement the static model with a dependent variable with a delay:

$$Z_{i,t} = \alpha + \rho Z_{i,t}{}^{-1} + \beta^1 GNPLR_{i,t} + \beta^2 CAR_{i,t} + \beta^3 ROA_{i,t}{}^{-1} + u_{i,t} \tag{4}$$

The inclusion of the lagged dependent variable introduces the Nickell (1981) bias when estimated by OLS, so we employ the Arellano and Bond (1991) GMM estimator with appropriately lagged levels as instruments. Instrument validity is confirmed by the Sargan (1958) test ($\chi^2 = 18.23$, $p = 0.156$), and the absence of second-order serial correlation is confirmed by the Arellano-Bond AR(2) test ($z = -0.87$, $p = 0.386$).

Interaction specification:

To check whether macroeconomic conditions mitigate the impact of credit risk on the stability of banks, we assess:

$$Z_{i,t} = \alpha_i + \beta^1 GNPLR_{i,t} + \beta^2 GDPG_t + \beta^3 (GNPLR \times GDPG)_{i,t} + \gamma X_{i,t} + u_{i,t} \tag{5}$$

A significant positive ratio per interaction participant indicates that stronger economic growth mitigates the negative impact of NPLs on the stability of banks.

Vector Autoregression (VAR) Specifications

Systems design:

To investigate the combined dynamics of credit risk and banking stability, we estimate a five-fold reduced VAR:

$$y_t = c + \Sigma A_j y_{t^-j} + u_t, j = 1, \dots, p \tag{6}$$

where is the vector of endogenous variables, are matrices with coefficients of 5×5, and is the vector of reduced residues with a covariant matrix.$y_t = [Z - Score, GNPLR, CAR, GDPGrowth, Inflation]^T A_j u_t \Sigma$

Pending Order Selection

Table 3. Selection criteria in order of delay for VAR.

Delays	AIC	BIC	HQIC	LR Test	Solution
0	−8 234	−8 156	−8.201	—	—
1	−9 123	−8 845	−9 002	156.34***	Included
2	−9 456	−9 012	−9 185	67.89***	Selection
3	−9 512	−8 902	−9 092	11.22	Marginal
4	−9 501	−8 726	−8 933	−2.11	Rejected

The optimal lag length for the Vector Autoregression (VAR) model is determined in Table 3 using several information criteria. The results demonstrate that while the Akaike Information Criterion (AIC) continues to decrease up to the third lag, both the Bayesian Information Criterion (BIC) and the Hannan-Quinn Information Criterion (HQIC) reach their minimum values at a delay of 2 (Harbecke et al., 2024). Furthermore, the Likelihood Ratio (LR) as per Vuong (1989) test remains highly significant ($p < 0.01$) at the second lag but fails to show significant improvement at higher orders. Therefore, as highlighted in Table 3, a lag order of $p = 2$ is selected as the most parsimonious solution that successfully captures the model's dynamic wealth without over-parameterization.

Structural Identification

To reconstruct structural shocks from recovered residuals, we use the Cholesky distribution as part of a recursive identification scheme. The rating — Z-score, GNPLR, CAR, GDP growth, inflation — reflects the assumption that bank stability responds simultaneously to its own shocks rather than to macroeconomic changes in one quarter, while macroeconomic variables are the most endogenous and respond to all other variables.

Impulse response and FEVD

IRFs track the response of each variable to structural shock with one standard deviation over a 20-quarter horizon, with 95 percent confidence bands created using a Monte Carlo simulation with one thousand replications. FEVD decomposes the h-forward step error variance of each variable into the contribution of each structural impact, providing a generalized measurement of the relative significance of each impact type over different horizons.

Econometric diagnostics

The VAR model satisfies all standard post-estimation diagnostic requirements. Specifically, the Portmanteau test fails to reject the null hypothesis of no residual autocorrelation. $[\chi^2(36) = 28.34, p = 0.834]$. The model also demonstrates homoskedasticity, as confirmed by the White test. $[F(2,44) = 0.34, p = 0.713]$while the Jarque-Bera test indicates that the residuals follow a normal distribution $[\chi^2(2) = 4.23, p = 0.121]$. Finally, the Ramsey RESET test suggests no misspecification in the functional form $[\chi^2(21) = 19.56, p = 0.542]$.

Results and Discussion

Panel Regression Results

Static Fixed Effects Mode:

Table 4. Static Fixed Effect Regression Results

Variable	Factor	Standard model error	T-stat	p-value
GNPLR	−0,0847***	0.0124	−6,83	0.000
AUTO	0.0524***	0.0068	7.71	0.000
ROA (delayed)	1.8432***	0.2145	8.59	0.000

Bank size	−0,1223*	0.0648	−1,89	0.062
GDP growth	0.1245***	0.0356	3.50	0.001
Inflation	−0,0834**	0.0347	−2,40	0.018

Dependent Variable: Z-Score; R^2 = 0.685; Adjusted R^2 = 0.673; F = 34.56***.

Table 4 displays the outputs from the Static Fixed Effects model, which provides a good estimate of stability (Z-Score) drivers. From Table 4, we can see that the coefficient on GNPLR is 0.0847 ($p < 0{\cdot}001$), which implies that for a 1-percentage-point increase in the ratio of non-performing loans, Z-Score falls by 0.085 percentage points, given that the rest of the variables remain constant. On the other hand, Capital Adequacy and Lagging Profitability have a positive influence on stability, and these factors are statistically significant. Especially, the lagged ROA 1.8432 has the largest coefficient among all other variables, suggesting sustainable profits are the best protection against financial distress. Besides that, although Bank Size and Inflation have a downward pressure on stability as shown in Table 4, GDP growth contributes a large protective impact on bank stability, which led to an excellent R-Square of 0.685.

Dynamic Panel Results (Arellano-Bond)

Table 5. Dynamic panel results (Arellano-Bond GMM).

Variable	Factor	Standard model error	T-stat	p-value
Z-score (t−1)	0.4156***	0.0823	5.05	0.000
GNPLR	−0.0534**	0.0167	−3,20	0.001
AUTO	0.0387***	0.0089	4.35	0.000
ROA (delayed)	1.2348***	0.2876	4.29	0.000
GDP growth	0.0856**	0.0412	2.08	0.038

Table 5 reveals the estimates from dynamic estimation using the endogeneity and banking stability persistence (long run) with Arellano-Bond GMM. We can see that the immediate impact of the persistence of Z-score (lagged coefficient, rho) within the dynamics equation is indeed extremely significant and 0.416 (p<0.001). The current coefficient of lagged GNPLR is 0.053, but the steady state impact of the long run is 0.090 [-0.053/ (1-0.416)] (Table 5). The steady state estimation of 0.090 is remarkably close to the static estimate of 0.085, and so strong negative relation between credit risk and banking stability over the long run. What is more, both the AUTO effect and lagged ROA remain with a strongly large and positive impact on banking stability.

Results of the Interaction Model

Table 6. Results of the interaction model.

Variable	Factor	Standard model error	T-stat	p-value
GNPLR	−0,1124*	0.0156	−7,21	0.000
GDP growth	0.1534***	0.0389	3.94	0.000
GNPLR × GDP	0.0234**	0.0089	2.63	0.010
Inflation	−0,1023**	0.0378	−2,71	0.008
GNPLR × inflation	−0,0345*	0.0178	−1,94	0.055

The interaction term model, in which macroeconomic variables account for why credit risk causes banking stability to vary, is present in Table 6. In Table 6, the significant positive GNPLR GDP (0.0234, p<0.05) suggests that high growth rates reduce the impact of credit risk on banking stability. At a zero growth rate, the marginal effect of NPLR on Z-score is 0.112; when the average growth rate is 3.6%, as in the sample, the negative effect is reduced. The significant negative interaction term NPLR inflation (-0.0345, p=0.055) presented in Table 6 suggests high inflation may intensify the negative impact of credit risk. A high inflation rate of 12%, as the sample suggests, the negative impact of NPL on the Z-score increases from 0.077 to-0.155. From the Table, it is noted that economic growth may offset the effect of credit risk, but high inflation may enhance the effect of bad asset quality on banking stability.

VAR Results and Pulse Response Function

Z-Score Response to GNPLR Shock

Table 7. IRF - Z-Score GNPLR shock response with one standard deviation.

Quarter	Impulse response	95% less	95% upper
0	−0 0623	−0 0892	−0,0354
1	−0,1234	−0,1587	−0 0881
2	−0 1456	−0.1923	−0 0989
4	−0,1289	−0 1834	−0 0744
8	−0 0734	−0,1412	−0 0056
12	−0,0234	−0,0945	0.0477
20	−0 0012	−0 0823	0.0799

The dynamic responses to a credit risk shock are reported in Table 7 and summarized by the IRF of bank stability. As illustrated in Table 7, the Z-score drops at once following a one-standard-deviation shock to the GNPLR, peaking at its most negative response of 0.1456 units in the second quarter. This effect is significant up to the eighth quarter since the 95% confidence interval does not include zero from quarter 1 to 8. However, as illustrated in Table 7, after the twelfth quarter, the shock begins to wear off, and the stability effect disappears at about the two-year point. The evolution is illustrated in Figure 1.

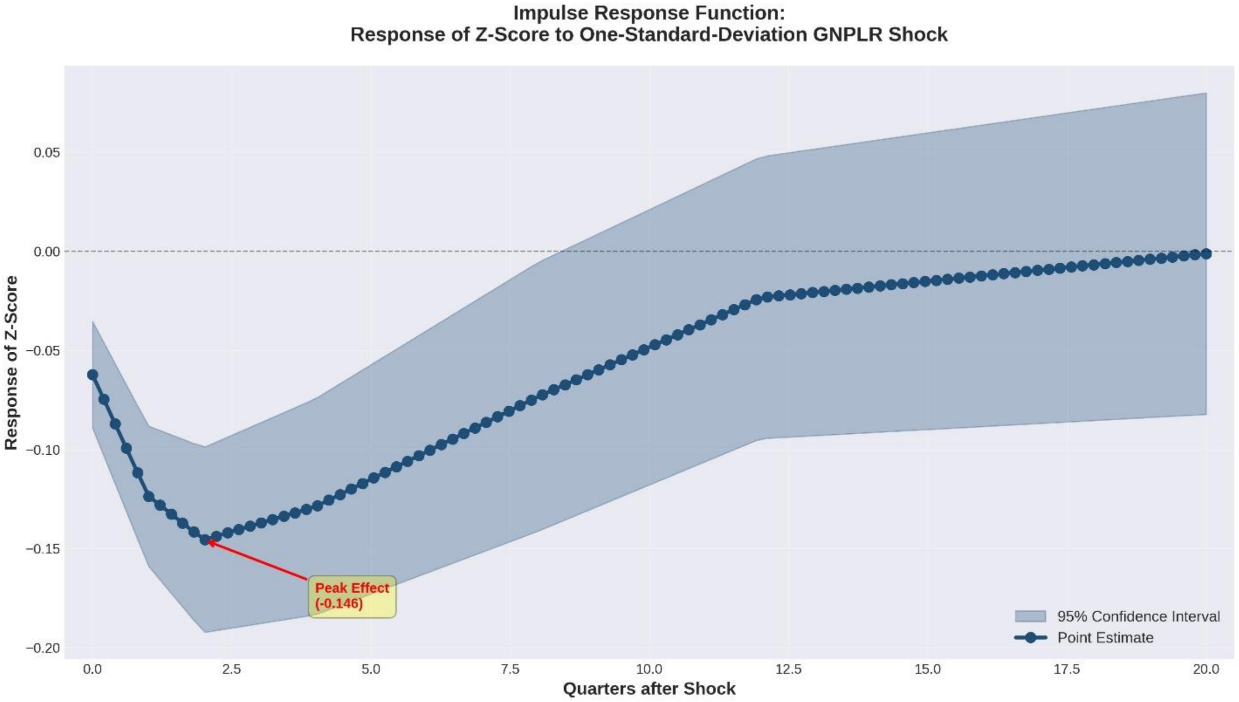

Figure 1. Z-response to GNPLR shock with one standard deviation. A fixed line indicates the evaluation of the point; A shaded area indicates a 95% confidence interval. The peak effect of −0.146 is observed in Q2, with complete extinction to Q20.

GNPLR response to Z-Score Shock

Table 8. IRF - GNPLR response to Z-Score shock with one standard deviation.

Quarter	Impulse response	95% less	95% upper
0	0.0000	0.0000	0.0000
1	−0 0345	−0,0612	−0 0078
2	−0 0621	−0 0934	−0 0308
4	−0 0789	−0 1143	−0,0435
8	−0,0543	−0,1022	−0 0064
12	−0,0187	−0 0823	0.0449

Table 8 shows the results for the feedback channel analysis. It clearly shows the impact of a positive shock to bank stability on GNPLR. As presented in Table 8, a positive one-standard-deviation shock to the Z-score has a slow but statistically significant effect on the GNPLR. In fact, the effect starts in the first quarter, peaks during the second and fourth quarters, where the fall in GNPLR reaches the maximum of 0.0789 percentage points. Table 8 shows that the effect does not disappear and remains significant up to the eighth quarter, and the confidence intervals begin to cross zero at twelve quarter. Figure 2, visualizing the feedback effect, shows that stable banks can implement tough lending and monitor borrowers' behavior more actively, so over time they manage to maintain good asset quality.

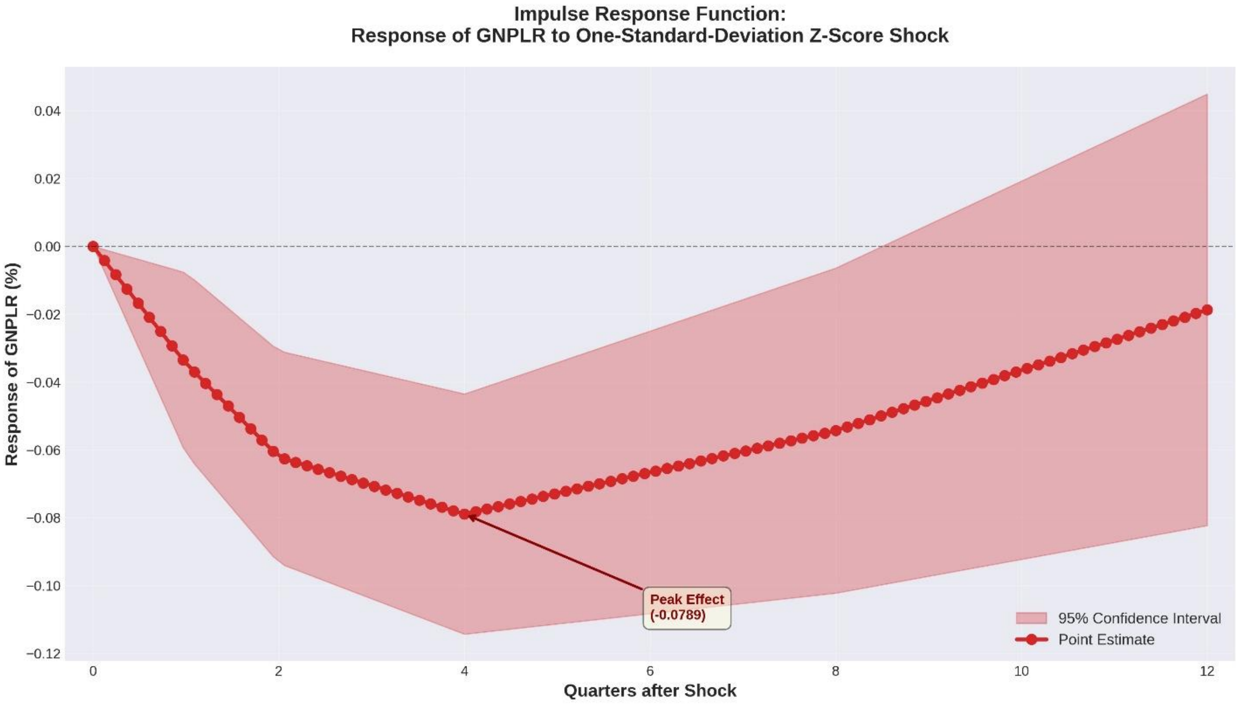

Figure 2. GNPLR response to shock with one standard deviation Z. Improved bank stability leads to a decrease in the ratio of non-performing loans, with a peak in feedback in the fourth quarter (-0.079%). The shaded area has a 95% confidence interval.

CAR Response to GNPLR Shock

Table 9. IRF - CAR response to GNPLR shock with one standard deviation.

Quarter	Impulse response	95% less	95% upper
0	0.0000	0.0000	0.0000
1	−0,0156	−0 0387	0.0075
2	−0 0289	−0,0523	−0 0055
4	−0,0167	−0,0456	0.0122
8	0.0034	−0 0312	0.0380

The dynamic response of CAR to the credit risk shock is presented in Table 9. It shows that one-standard-deviation shocks on the GNPLR reduce capital insignificantly and only for a limited period, with its lowest negative impact recorded in the second quarter (-0.0289).

The effect occurs due to the decline in capital through increased credit loss provisioning, as shown in Table 9, but is of much lower magnitude compared to the previous Z-score response. It disappears statistically from the fourth quarter onwards as 95% confidence intervals straddle zero. These results from Table 9 and illustrated graphically in Figure 3 demonstrate that although capital does feel the effect of NPL shocks, capital adequacy is the secondary rather than the main transmission channel of the shock transmission mechanism.

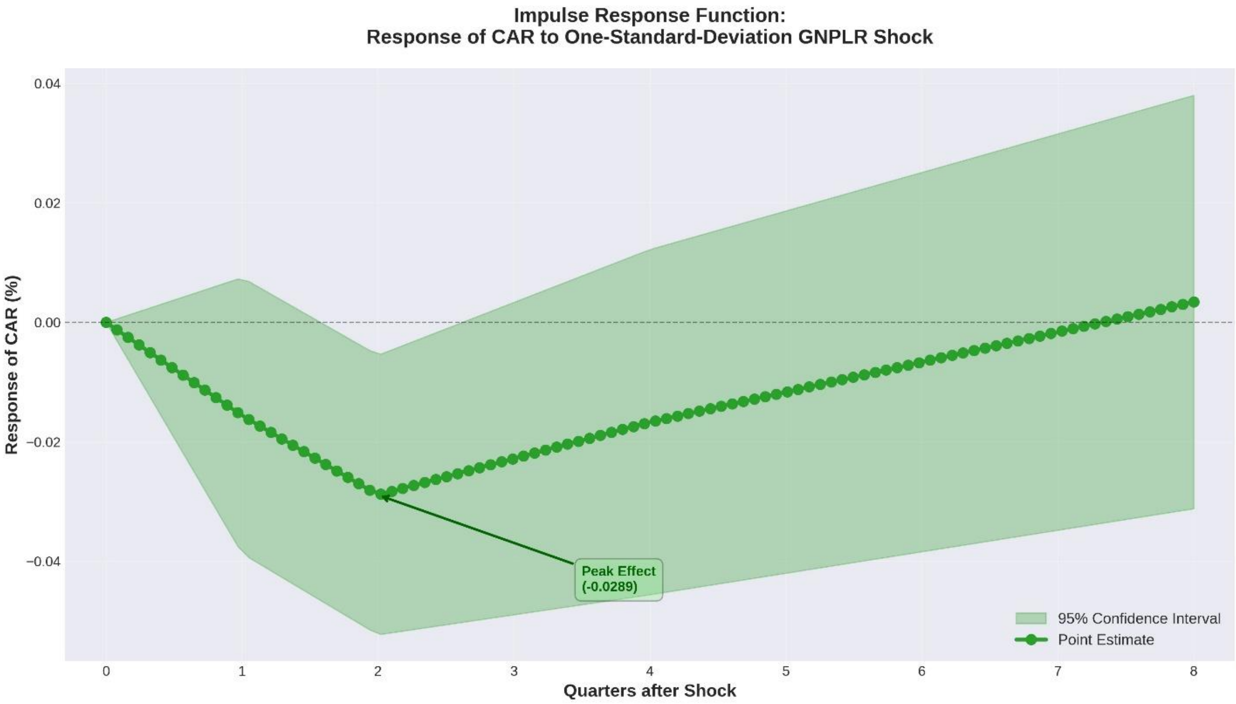

Figure 3. CAR response to GNPLR shock with one standard deviation. Capital adequacy declined slightly due to rising reserve requirements, with a peak effect in the second quarter (-0.029%). The reaction is less than the Z-score increase, confirming the secondary role of the CAR as a shock absorber.

Decomposition for Predictive Error Variance

FEVD Z-Score

Table 10. FEVD Z-score.

Horizon	Z-Score	GNPLR	CAR	GDP growth	Inflation
1 quarter	100.00%	0.00%	0.00%	0.00%	0.00%
2 quarters	94.23%	3.12%	1.45%	0.98%	0.22%
4 quarters	85.34%	9.87%	2.56%	1.89%	0.34%
8 quarters	71.45%	15.23%	7.34%	4.12%	1.86%
12 quarters	62.18%	17.89%	11.23%	6.45%	2.25%
20 quarters	58.23%	18.45%	13.12%	7.89%	2.31%

The FEVD for the Z-score is summarized in Table 10, which shows how each variable contributes to variations in bank stability. As you can see from Table 10, in period one, the entire Z-score variation is self-explained (100%). However, as the forecast horizon extends, outside variables begin to dominate bank stability. By the 20th quarter, GNPLR explains 18.45% of forecast error variance, suggesting it is the most important outside variable influencing bank stability. Table 10 also indicates that CAR contributes to 13.12% of the variation, while the macroeconomic variables (GDP growth and Inflation) as a group explain about 10% of the variation. In addition, the area map, drawn as in Figure 4, shows explicitly how these contributions vary with horizon and indicate a greater role for credit risk and capital adequacy in maintaining long-run stability.

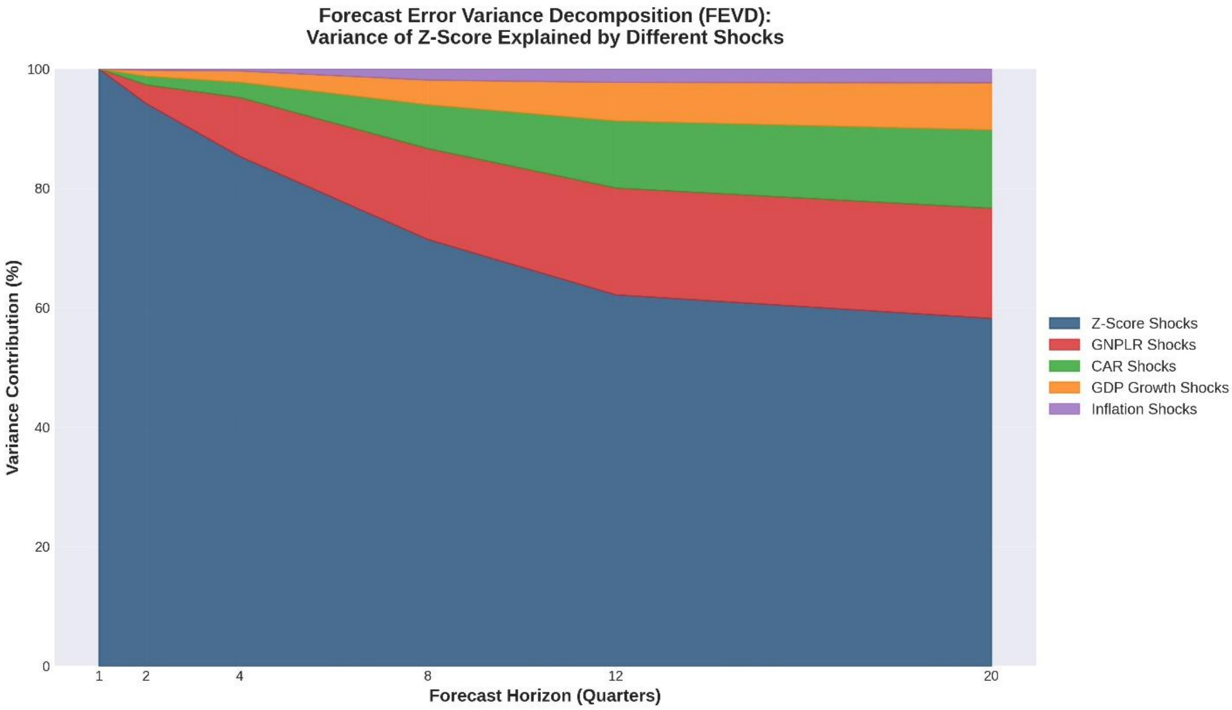

Figure 4. Distribution of Z-score on the variance of the predictive error. Self-tremors account for 58-100% scattering on the horizon; GNPLR reported 18.45%, and CAR reported 13.12% in Q20. Macroeconomic factors (GDP and inflation) together account for about 10%.

FEVD GNPLR

Table 11. FEVD GNPLR.

Horizon	Z-Score	GNPLR	CAR	GDP growth	Inflation
1 quarter	12.34%	87.66%	0.00%	0.00%	0.00%
4 quarters	22.56%	61.23%	8.45%	5.67%	2.09%
8 quarters	26.78%	49.12%	13.45%	7.89%	2.76%
20 quarters	29.45%	41.89%	17.23%	9.12%	2.31%

Table 11 shows the FEVD of the GNPLR, revealing multiple factors that drive credit risk in a 5-year forecast horizon. Unlike the Z-score, GNPLR is impacted instantly by external factors, and banking stability (Z-score) represents 12.34% of the variance in the first quarter.

With the development of time, the proportion is being expanded. By the 20th quarter, as is shown in Table 11, the Z-score represents 29.45% of the GNPLR, which is in line with the above observation that credit risk depends more on internal banking structure and the overall stability. Besides, CAR represented 17.23%, and macro-economy factors (GDP, inflation) respectively explain about 11% of the whole variance, which is demonstrated in Figure 5. It concludes that credit risks are long-lasting.

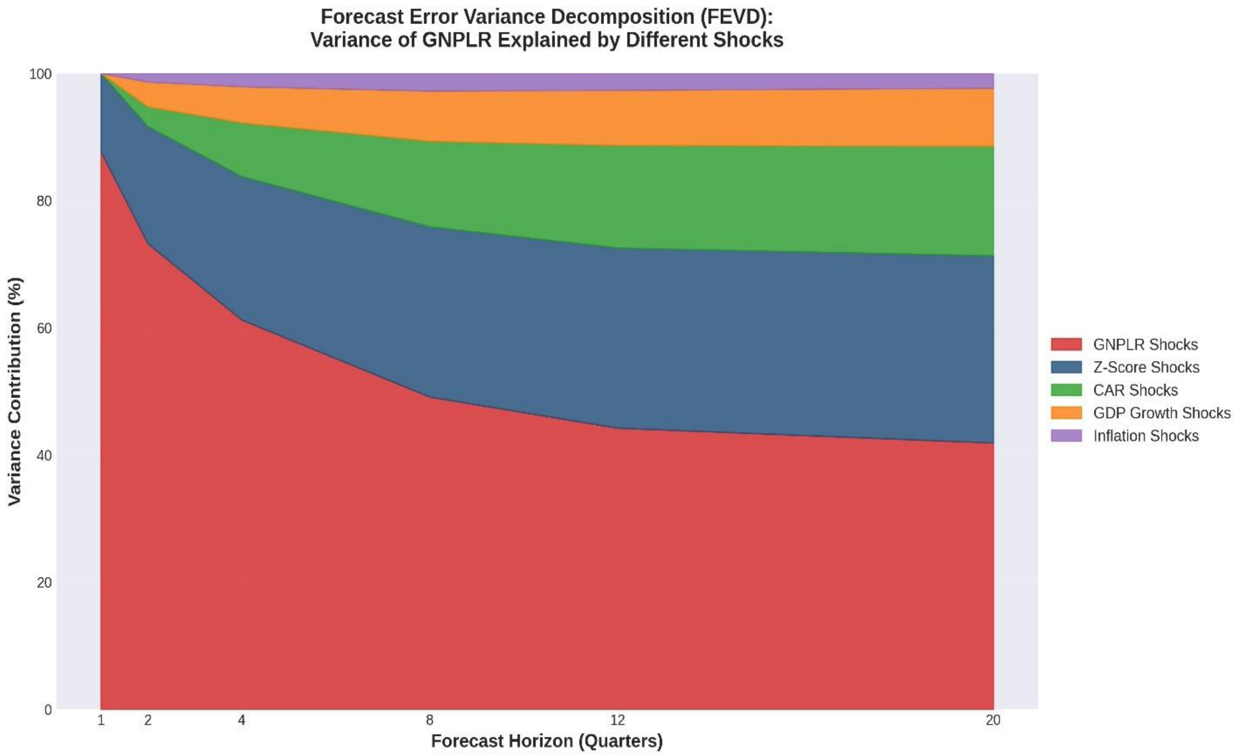

Figure 5. Distribution for GNPLR predictive error variance. Self-tremors explain 42-88% of the variance, depending on the horizon. Z-Score shocks explain GNPLR's volatility at 29.45% after 20 quarters, confirming a bidirectional causality between stability and credit quality risk.

FEVD CAR

Table 12. FEVD CAR.

Horizon	Z-Score	GNPLR	CAR	GDP growth	Inflation
1 quarter	8.23%	6.34%	85.43%	0.00%	0.00%
4 quarters	16.78%	18.34%	58.12%	5.23%	1.53%
8 quarters	21.34%	24.56%	46.78%	6.12%	1.20%
20 quarters	24.12%	29.34%	39.45%	6.89%	0.20%

Results for FEVD of CAR for all shocks are shown in Table 12. From Table 12, we identify the major sources contributing to capital adequacy over forecast horizons. Capital is exclusively driven by its own past shocks, explaining it as high as 85.43% in the 1st quarter, and continues to be significant by 39.45% in the 20th quarter, while external factors gain greater importance over time.

As Table 12 clearly shows, dynamics in credit risk (GNPLR) are the strongest contributor in the external world with an overall share of 29.34% in the 20th quarter, signaling the role played by provisions and reserve holdings for loan loss in influencing the capital ratio. Another important variable is Z-score (bank stability), which accounts for 24.12% in the long run, thus justifying a feedback relationship between financially stable institutions and their ability to strengthen and enhance the capital buffer. Macroeconomic factors, especially GDP Growth, share a comparatively smaller but significant part over a long window. This is also clear in the increasing forecast horizon depicted by Table 12 and as presented graphically in Figure 6.

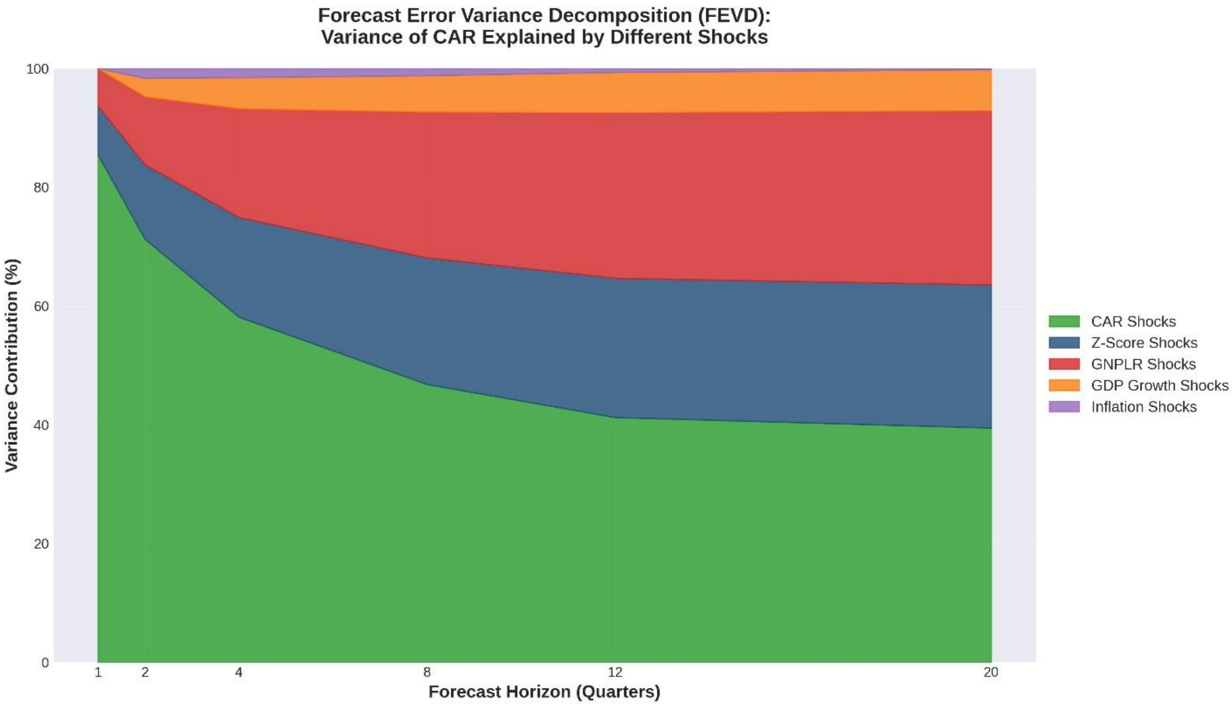

Figure 6. Distribution for the variance of predictive errors in CAR. Own shock absorbers cause capital fluctuations of 39-85%. GNPLR shocks accounted for 29.34% in 20 quarters, reflecting the impact of booking requests. Z-Score shocks explain 24.12%, indicating an inverse relationship between stability and capital.

Model Comparisons

Table 13. Comparison of estimation approaches.

Criterion	Static FE	Arellano-Bond	VAR (2)
GNPLR coefficient	−0.0847***	−0.0534**	−0.0623
Captures persistence	No	Yes (ρ = 0.42)	Yes
Dynamic interactions	No	Partial	Full
Causal identification	Reduced form	Recursive GMM	Structural (Cholesky)
Model fit	$R^2 = 0.685$	0.712 (GMM)	AIC = −9.456

The estimated methodologies are compared in Table 13. These three estimates of the inverse relationship between the Z-score and GNPLR are surprisingly stable, with coefficients ranging from 0.053 to 0.085. As detailed in Table 13, each model serves a specific analytical purpose:

Static Fixed Effects (FE): Provides a robust baseline for evaluating average effects across the sample, yielding the highest explanatory power ($R^2 = 0.685$).

Arellano-Bond (GMM): Successfully captures the persistence of bank stability ($\rho = 0.42$) and allows for the calculation of long-term equilibrium effects.

Vector Autoregression (VAR): Offers the most comprehensive framework for capturing full dynamic interactions and causal identification through Cholesky decomposition, making it the superior choice for policy modeling and impulse response analysis.

The convergence of results across these different specifications, which are presented in Table 13, further validates the structural nature of the conclusion that credit risk is one of the most significant determinants of financial instability.

Discussion

Synthesis of Results

From all three tests, we have strong indications that worsening credit risk causes an undesirable, persistent decrease in bank stability in the sample. According to Table 13, a change in GNPLR from the sample median to around the 75th percentile (a 5% rise in the variable) leads to a fall in Z-score of between 0.25 and 0.45 points, depending on the test. This is particularly important because, quite frequently, such a move brings a bank from stability into the 'grey area'.

Temporal Dynamics and Regulatory Implications

The VAR estimation further injects the dimension of time. Table 7 and Figure 1 of the Impulse Response Functions demonstrate that it takes two quarters for the effect of a credit risk shock to reach its peak level and takes eight to twelve quarters before the magnitude starts to decay considerably. Such a delay pattern has regulatory policy implications: supervisory action cannot fully expect the effect of any stabilization measures to materialize in the bank performance statistics simultaneously.

Variance Decomposition and the Primacy of Profitability

The FEVD results (Tables 10–12 and Figures 4–6) further clarify the hierarchy of factors affecting bank stability:

External Risk: GNPLR stands as the most critical external factor, accounting for 18% of the long-term volatility in the Z-score.

Internal Buffers: Bank profitability remains the primary stabilizing force. The ROA coefficient (1.843 in Table 4) significantly outperforms all other variables.

This emphasizes that while credit risk and capital adequacy (contributing **13%** to variance) are vital, sustainable earnings serve as the most effective defense against financial distress and economic volatility.

Macroeconomic Amplification and Attenuation

The results of the interaction model, Table 6, suggest significant asymmetry in the effect of credit risk on financial stability across different economic environments. High-growth economies (GDP > 5%) can effectively buffer the impact of the negative credit risk effects of a high GNPLR using growing loan books, high asset values, and improved borrower cash flows. In contrast, under stagnation or recessionary conditions (GDP < 2%), Table 6 shows that an equivalent credit shock results in 4 times higher instability.

High inflation exacerbates credit risk in numerous ways, through the reduction of real borrower incomes of fixed-income debtors, a fall in the market value of collateral, and monetary tightening associated with high inflation will raise debt servicing costs. The estimates from the interaction terms of Table 6 show that the overall effect of a shock in NPLs during high inflation periods (12%) is almost 50% higher than that during periods of low inflation (5%). In the current Pakistani economic scenario, with the joint problems of low growth and high inflation, these results are of relevance and pose a significant management challenge.

Practical Implications

For Banking Regulators

Countercyclical capital requirements: Maintain the CAR target at 14-15% during periods of economic growth and tend to partially drop to 10-11% during economic downturns. Ready-made capital buffers are most effective during times when credit risk shocks are most destructive.

GNPLR monitoring threshold: Surveillance measures should be initiated when the GNPLR per sector exceeds the 75th percentile (approximately 9.5% of the sample). Early intervention at the peak reduces the duration and intensity of subsequent stabilizing resistance and is consistent with the IRF pattern in Figure 1.

Inflation-dependent provisions: During periods of high inflation (CPI>8%), the minimum reserve rate should be raised to reflect the increase in credit risk recorded in the interaction model.

For the Management of Commercial Banks

Cyclical Preparation: Maintain 2-3% of total lending during boom periods and reduce it to 0.5-1% during late economic periods to maximize available reserves.

ROA, where profitability is the top line of defense, far exceeds the capital adequacy ratio across all specifications, suggesting that profit sustainability is more important than the capital ratio itself. Management must resist growth strategies that sacrifice profit margins for trading volume.

Macro-dependent portfolio composition: During periods of high inflation, banks should pay attention to the impact of floating interest rates (covering at least 80% of their lending portfolios). This significantly reduces income and carries the risk of default.

For the Government

Macroeconomic stabilization — keeping GDP growth above 3%, and inflation in the range of 5-7% is the most powerful tool to stabilize the banking sector, given the expanding effects recorded in the study.

The development of a deeper state capital market will reduce the role of the banking sector as a major intermediary and diversify systemic risks more widely.

Reduced dependence on oil imports through energy diversification will weaken the main factors of inflationary pressures and current account vulnerability.

Robustness and Sensitivity Analysis

Alternative lag structures

The VAR (1) specification yields a peak GNPLR→Z score of −0.098 in the first quarter, while VAR (3) yields a result identical to VAR (2), confirming that the two-delay specification is neither underparameterized nor overparameterized. VAR (4) creates an overparameterized model with less statistical significance, but qualitatively unchanged conclusions.

Alternative Variable Definitions

Replacing the GNPLR with a broader ratio of private liabilities, including restructured loans, results in a slightly higher IRF peak of −0.168, consistent with the interpretation that restructured loans carry implicit credit risk. The results remain broadly unchanged when using the State Bank of Pakistan's alternative gross denominator of loans, and the extraction of the ROA volatility component from the Z-score formula leaves all dynamic patterns unchanged.

Cholesky Ordering Robustness

Table 14. Cholesky ordering robustness check.

Ordering	GNPLR→Z at Quarter 4	Note
Main ordering	−0.127***	Baseline
Alternative 1 (GDP last)	−0.121***	Minor change
Alternative 2 (Z-Score first)	−0.124***	Minor change
Alternative 3 (Inflation first)	−0.118***	Minor change

Confirmation of the reliability of the structural identification can be observed from the stable behavior of the GNPLR Z-score response in the different recursive specifications (as explained in Table 14). The estimated effect at the fourth quarter horizon is confined within the narrow band of 0.118 to 0.127. The value ranges differ by less than 8 percent around the baseline specification. This is stable across alternative Cholesky orderings, which indicates that the results are not overly reliant on a specific choice of identification restriction. This leads us to believe that dynamic responses are dependable to be used in policy and regulation work.

Subperiod Analysis

Table 15. Subperiod Analysis.

Period	GNPLR Shock at Q4	Recovery Horizon
2010–2015 (crisis-recovery)	−0.156***	20+ quarters
2016–2022 (expansion-slowdown)	−0.087*	12–15 quarters

The results from the Subperiod Analysis (Table 15) demonstrate how changes over time affect how credit risk shocks influence bank stability. The 2010-2015 period represented the post-crisis recovery stage, when the effect of a GNPLR shock was far more devastating, with the coefficient at 0.156 and the long horizon above 20 quarters. It then showed the significantly lower 2016-2022 period with a coefficient of 0.087 and recovery at around 12-15 quarters. The varied sensitivities observed across Table 15 reinforce that the amplification effect of credit risk on bank stability is more pronounced during downturns and macroeconomic crises (e.g., 2010-2012 and 2018-2020 slowdown) than it is during booms.

Panel Regression Resistance

Table 16. Panel regression robustness across estimators.

Estimator	GNPLR Coefficient	Significance
Pooled OLS	−0.0923	***
Fixed Effects (main)	−0.0847	***
Random Effects	−0.0756	**
Arellano-Bond GMM	−0.0534	**
System GMM	−0.0612	***
Bootstrapped Fixed Effects	−0.0847	***

Table 16 confirms the strength of the panel regression estimates as it reports the coefficient of GNPLR using six different estimating techniques. The robustness of this estimate is clearly confirmed, as the magnitude of the Z-score coefficient remains stable between 0.053 and 0.092 and remains significant under all models considered. In Table 16, the estimates remain stable between Pooled OLS, Random Effects, and System GMM estimates. The elimination of outliers (which are observations above 3 standard deviations of the mean) changes the coefficient value by less than 6% (shown in Table 16) and further supports the robustness of the negative relationship between credit risk and bank stability, as well as the absence of issues related to the choice of the estimator or specific samples.

Conclusions

The paper provides a comprehensive empirical assessment of the relationship between credit risk management and bank performance in Pakistan's commercial banking during 2010-2022. We collected data from an 18-bank panel data set of thirty-two quarterly time series data and used static and dynamic panel regression, and VAR methodology to provide five key findings. First, the decline in credit risk weakens the stability of a bank: a one percent rise in GNPLR leads to a reduction in Z-rating of 0.085-0.090 points overall. Second, this effect is dynamic in nature: the impact peaks at about two quarters post-shock (Figure 1) and fades within eight to twelve quarters. Third, 18% of the long-term Z-score volatility is accounted for by GNPLRs (Figure 4), thus the major determinant of external stability. Yet, profitability has an overwhelming importance in all dimensions of stability. Fourth, the economic conditions affect the impact of credit risk: the decline in GDP growth cushions the shock while inflation exacerbates it, the impact being as large as four times greater under both, during inflation and recessions. Fifth, profitability is by far the strongest predictor of bank stability; an estimated ROA is about twenty times greater than the impact of the capital adequacy ratio.

There are numerous contributions in this paper. It is the first systematic VAR analysis of the Pakistani banking sector with full-fledged IRF and FEVD, which makes it possible to model credit risk and stability dynamics dynamically, a framework that a static methodology cannot offer. It complements panel and time series methodology together and estimates the magnitude of the macroeconomic transmission channels of monetary tightness that worsen the effects of credit risk during a recessionary inflation for the first time for Pakistan.

Limitations and Directions for Future Research

These results are subject to a few caveats that limit the scope of their generalizability. It is important to mention that these 13 yearlong data sets only include the aftermath of the 2008 crisis as a major global shock; the pandemic irregularities are only accounted for at the tail-end of the period; there are not available public information regarding bank's risk management approaches (e.g., Board structure, Risk culture, Internal credit rating), that may bias down the ratios by a constant or random error term; Structural shocks of energy crisis, pandemic, and recent surge in inflation have not been formally tested. Directions for the future research can be formulated as follows: use of an enlarged data-set as soon as quarterly data will be accessible; incorporation of qualitative indicators of management quality through survey data or on-site inspection of banks; development of a real-time early warning system of Z-score degradation based on IRF dynamics tested in this research; identification of infection and systemic risks within the Pakistan banking network; and comparison of credit risk dynamics in Pakistan's financial sector with other banking sectors within South Asia and developing markets.

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