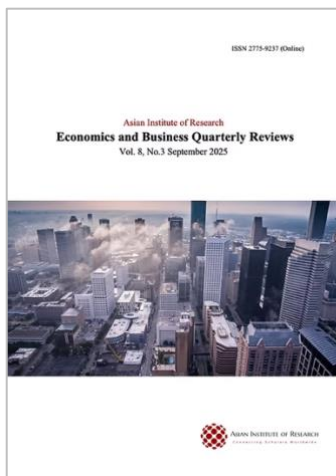




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Does Credit Growth Weaken Stability? Evidence and Policy Implications in Vietnam

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Abstract

This paper examines the bidirectional dynamics between credit growth and banking stability in the context of Vietnam, where the financial system is dominated by banks and the macroprudential framework is strongly strengthened over the period 2008–2024. Using a quarterly panel dataset of 29 Vietnamese commercial banks (Q1/2008–Q4/2024) and a Panel VAR (PVAR) model to handle endogeneity, the study quantifies the time-varying responses of credit growth (CRE) and the stability indicator Z-score to structural shocks. The main results show that: (i) a positive shock to banking stability increases credit in a statistically significant and persistent manner across multiple quarters; (ii) a credit growth shock does not have a significant impact on Z-score in the short–medium horizon; and (iii) the forecast variance decomposition (FEVD) shows asymmetry: Z-score variation is largely “autogenerated”, while CRE variation is increasingly explained by stability shocks (approximately 9–10% in the 10th quarter). Granger causality tests confirm a unidirectional relationship from stability to credit. The findings imply a “stability-first, credit-quality-later” policy priority order: strengthening capital and earnings quality, cross-cyclical provisioning discipline, and maintaining macroprudential tools that help expand credit supply sustainably without sacrificing systemic safety. The study contributes quantitative evidence in emerging markets, complementing the international literature that often emphasizes the credit-to-crisis channel, and suggests extensions to nonlinearities/thresholds and bank-specific heterogeneity.

Keywords: Banking Stability (Z-score), Credit Growth; Panel VAR (PVAR), Macroprudential Policy, Granger Causality, Impulse Response Functions (IRF), Forecast Error Variance Decomposition (FEVD), Vietnam

1. Introduction

In highly banked emerging market economies such as Vietnam, credit growth is both an important driver of economic growth and a potential source of financial cycle risk. The financial accelerator framework predicts that the health of banks’ balance sheets—through capitalization, earnings quality, and earnings volatility—regulates the cost of capital, risk appetite, and thus directly influences credit supply. Conversely, hot credit cycles, especially when concentrated in risky assets, can erode stability through loosening of credit standards, leverage accumulation, and maturity mismatches. This bidirectional relationship makes identifying the dominant transmission path and the lag of the impact a central question for policymakers and bank managers. During the 2008–2024 period, the Vietnamese banking system underwent extensive adjustment phases: post-global financial crisis, restructuring of weak credit institutions, implementation of Basel II and gradual approach to

Basel III, tightening of debt classification and provisioning, and coping with and recovering from the COVID-19 shock. Along with the fluctuations in sensitive segments such as real estate and corporate bonds, highlighting the role of macroprudential tools (concentration limits, risk weights, capital requirements/structural liquidity) in smoothing the credit cycle. This context provides a “natural laboratory” to test: (i) whether the shock to improving banking stability leads to credit expansion in reality; and (ii) whether the credit growth shock soon reflects into a weakening of stability in the short-to-medium term horizon, or is “neutralized” by institutional safety buffers.

In terms of measurement, the study uses Z-score as a bank-level stability measure—a “distance to default” indicator that combines profitability, capitalization, and profit volatility—and credit growth (CRE) as a measure of credit supply behavior. Z-score has the advantage of being cross-bank and time-varying, and directly reflects the three pillars of risk tolerance. However, since Z-score is a composite indicator, short-term effects from credit may be “masked” if profits temporarily improve; therefore, a time-varying dynamic analysis is necessary to avoid the illusion of instantaneous relationships.

In terms of methodology, to handle two-way endogeneity and slow feedback dynamics between variables, the study chooses a Panel VAR (PVAR) model. This approach treats all variables as endogenous, exploits time-varying information and bank-to-bank heterogeneity, and provides post-estimation tools such as impulse response functions (IRFs), forecast error variance decomposition (FEVDs), and Granger causality tests. Prior to estimation, the study conducts cross-sectional dependence tests (common in banking data due to systemic shocks and interconnections), unit tests (with second-generation CIPS), optimal lag selection according to the information criterion, and GMM diagnostics (AR(2), Hansen) to ensure model stability and instrument validity. On that basis, IRFs help quantify the “pathway” and persistence of the impact; FEVDs indicate the relative importance of each shock in explaining the forecast variation of the remaining variable; and Granger tests help establish the dominant forecast direction in the data.

The study contributes in three ways. First, at the empirical level, it provides new evidence in Vietnam — an emerging market — that bank stability shocks are predictive drivers of credit expansion, while credit shocks do not significantly shift stability over the short–medium horizon. This result is consistent with financial amplifier theory (where stability is a background condition for credit supply) and with the Vietnamese context where macroprudential buffers have been strengthened after the restructuring period. Second, at the methodological level, the study illustrates a “standard” PVAR procedure for bank data: cross-sectional dependence treatment, mixed integration order, lag selection, and rigorous GMM diagnostics — thereby providing a reference framework for further applications (addition of exogenous macro variables, nonlinear/threshold tests, bank clustering). Third, at the policy level, the finding of “stability → credit” and asymmetric FEVD implies that the order of priorities: capital consolidation, provisioning discipline, and risk management (i.e. improving stability quality) is the sustainable path to credit expansion, rather than loosening safety barriers or “pushing” credit by administrative orders.

From a policy perspective, the message of “building a stable foundation for credit to go further” is highly operational. As stability indicators improve, supervisors can expect credit to respond in an expansionary direction over the next few quarters; this helps coordinate monetary policy–macroprudential policy: in a favorable period, prioritize building buffers (adjusting risk weights, capital/liquidity requirements, strengthening loan classification standards); in a difficult period, use buffers to “absorb shocks” while maintaining essential credit flows. At the bank level, the governance implications are to invest in quality Tier 1 capital, stable core income, quantitative risk appetite, and portfolio-based early warning systems to avoid “silent” loosening of credit standards in the face of intense competition.

The remainder of the paper is organized as follows. The next section presents the theoretical framework and research overview, clarifies the transmission channels, and forecasts the expected sign/lag of the impact. Then, the Data and Methodology section describes the dataset of 29 commercial banks by quarter for the period 2008–2024, defines variables and the PVAR estimation procedure. The Results section presents the model stability diagnostics, IRF, FEVD and Granger tests. The Discussion section explains the economic mechanism, puts it in

the context of Vietnam and draws policy implications. Finally, the limitations and suggestions for extension (nonlinearity/threshold, bank differentiation, adding exogenous macro variables).

2. Theoretical framework and literature review

In an economy where banks are the dominant financial intermediaries, the relationship between credit growth and banking stability is considered to be bidirectional, acting as both an antecedent and an endogenous outcome of financial cycles. The classic literature on “financial accelerators” shows that a strong financial sector balance sheet—through equity capital, retained earnings, and risk expectations—reduces the cost of external capital and compresses risk premiums, thereby boosting credit supply and investment (Bernanke, Gertler, & Gilchrist, 1999; Kiyotaki & Moore, 1997). When banks are stronger, their risk-taking capacity increases, limiting the leverage constraint and creating room for credit expansion; conversely, when balance sheet quality deteriorates, funding costs increase, capital constraints tighten, and the amplification declines in the downtrend. On this theoretical basis, banking stability is not only a policy goal, but also a key state variable that determines the strength of the credit channel over the cycle.

However, the reverse link—from credit to stability—does not always manifest itself immediately in consolidated stability measures. The “risk-taking channel” suggests that low interest rates, high competition, and expectations of rising asset prices lead to a gradual loosening of credit standards, a gradual deterioration in the quality of new assets, and a buildup of risk over time (Borio & Zhu, 2012). The history of credit cycles shows that rapid credit growth is a strong predictor of medium-term financial crises, but negative stability effects (e.g., capital cracks, earnings volatility, nonperforming loans) often manifest with a significant lag (Schularick & Taylor, 2012; Jordà, Schularick & Taylor, 2015). This implies that, viewed over a short horizon, the credit shock may not be large enough—or long enough—to move aggregate stability indicators like the Z-score, especially in the presence of macroprudential tools as “shock absorbers.”

On the positive side, micro evidence suggests that bank capital health and resilience are positively related to the ability to expand credit. Research on US banks shows that banks with strong capital and liquidity tend to increase their loan market share, especially during periods of stress (Berger & Bouwman, 2013). Other quantitative assessments (Berrospide & Edge, 2010; pooled 2018) indicate that a unit increase in capital, depending on the period and regulatory environment, is usually accompanied by a small increase in credit supply, although the sensitivity may be modest. From a policy perspective, the dynamic provisioning mechanism in Spain before the crisis and the subsequent countercyclical capital buffer (CCyB) approach in many countries were precisely designed to “inject” resilience during the boom phase and “drain” it during the bust phase, in order to both reduce the amplitude of the cycle and maintain the essential flow of credit to the real sector (Jiménez, Ongena, Peydró & Saurina, 2017; IMF SDN, 2012; BCBS/BIS guidelines). Thus, in an institutional framework where macroprudential tools are effective, short-term credit shocks are less likely to cause measurable volatility on the stability measure, whereas “stabilization” shocks are more likely to translate into credit expansion in the next few quarters.

A key issue in any attempt to quantify this relationship is the measurement of “bank stability.” The Z-score—defined as $(ROA + Equity/Assets)$ —is a measure of “distance to default,” closely aligned with the safety-first principle from Roy (1952). The higher the Z-score, the lower the probability that profits will fall sufficiently negative to destroy capital, and the more stable the bank (Laeven & Levine, 2009; Čihák & Hesse, 2010). The advantage of the Z-score is that it combines the three pillars: profit margin, capitalization, and profit volatility, making it suitable for cross-bank and time-series comparisons. However, it has its limits: if risk is “masked” by large short-term profit margins, the Z-score may be high but still imply potential vulnerabilities due to credit concentration, liquidity risk, or maturity mismatch. Therefore, many studies simultaneously retrieve auxiliary indicators such as non-performing loan ratio (NPL), capital adequacy ratio (CAR), structural liquidity ratio (NSFR, LCR), or even market measures such as risk beta, CDS spread or SRISK. In the context of Vietnamese data, Z-score is still a reasonable choice to represent “stable quality” at the listed bank level, as long as it is accompanied by sensitivity analysis and robust testing.

For credit, the common measure is the growth rate of outstanding loans (month/quarter/year), or year-over-year (YoY) growth to remove seasonal factors. At the system level, the BIS proposes the “credit-to-GDP gap” as a trigger indicator for CCyB, reflecting the difference between the observed credit/GDP ratio and the long-term trend. However, at the bank level, YoY growth of outstanding loans remains an informative indicator of credit supply behavior and lending strategies over time. A methodological note is to distinguish between “credit demand” (borrowing demand of businesses and households) and “credit supply” (lending policies and capacity of banks). Without survey data on demand over time, the observed variable of outstanding loan growth will be the result of both forces, and therefore the modeling framework must allow for two-way endogeneity.

The endogenous intertwining of credit and stability leads to the choice of a dynamic system of equations model, in which all variables are considered endogenous and react to each other through lags. The Panel Vector Autoregression (PVAR) method meets this requirement. PVAR allows simultaneous estimation on the banking panel, combining time series and cross-sectional differences, resulting in dynamic explanatory tools such as impulse response rate (IRF), forecast error variance decomposition (FEVD) and Granger causality tests. Common good practices include difference (or Helmert) transformations to remove fixed effects, using system/difference GMMs to handle endogeneity and instrumentation of lagged variables, choosing optimal lags according to information criteria (MAIC/MQIC/BIC), second-order autocorrelation diagnostics (AR(2)) and instrumentation validity tests (Hansen/Sargan), as well as cross-sectional dependence tests (Pesaran CD) to ensure that the error term assumption is sufficiently “nice” for inference (Love & Zicchino, 2006; Abrigo & Love, 2016; Arellano & Bond, 1991; Blundell & Bond, 1998; Pesaran, 2004). Another subtle aspect is shock identification in IRFs: with Cholesky ordering, for example, it is assumed that instantaneous changes in the preceding variable are not immediately influenced by subsequent variables in the same period. The choice of order may be based on economic reasoning: “stable” is the slower-changing state, so should it come before or after “credit”? The answer depends on the context; when the goal is to test both directions of transmission, it makes sense to test robustness with multiple identity configurations.

In the context of Vietnam, the banking market in the period 2008–2024 has gone through at least three prominent phases: (i) post-global crisis 2008–2011, with strong adjustments in asset quality and restructuring; (ii) period of strengthening the capital adequacy framework, implementing Basel II (capital standards, operational and market risk management) along with increased transparency requirements; (iii) exogenous shocks due to the COVID-19 pandemic 2020–2021 and post-pandemic recovery, parallel with rapid growth of consumer credit, real estate and corporate bond markets. These factors make “observed stability” vulnerable to both cyclical shocks and institutional adjustments. In fact, the current management method of the State Bank is to combine traditional monetary tools (operating interest rates, refinancing, required reserve ratio) with safety limits (risk coefficient for real estate/corporate loans, credit concentration thresholds, short-term capital ratio for medium- and long-term loans, etc.) to guide credit flows and reduce amplification. This creates a favorable context to test an important hypothesis: when the bank's “safety cushion” (capitalization, profit stability) is raised, how does credit supply tend to increase; and conversely, whether a “kick” in short-term credit will quickly respond to stability measured by the Z-score.

International evidence and theory suggest two hypotheses that underpin the dynamic analysis: First (H1), a positive shock to bank stability—increasing the Z-score through improved profit margins, capitalization, or reduced profit volatility—will relax capital constraints and reduce funding costs, thereby supporting credit growth in the next few quarters (Berger & Bouwman, 2013; Berrospide & Edge, 2010). Second (H2), a credit growth shock may not immediately weaken the Z-score over the short-to-medium term horizon, for two reasons: (a) the process of credit risk accumulation and asset quality deterioration is slow, often taking time to “freeze” on the income statement and balance sheet; (b) the presence of macroprudential tools (provisions, limits, risk weights) that act as “safety valves”, diverting some of the potential risks to capital buffers and early control mechanisms, thus smoothing the immediate impact (Borio & Zhu, 2012; Jiménez et al., 2017). This expectation map fits the financial cycle perspective: credit may be the “tincture” of instability in the medium term, but in the short term, if risk discipline is assured, we may not see a significant change in the stability measure immediately. From a measurement and data perspective, the choice of using a panel of listed banks is appropriate for the purpose of analyzing micro-dynamics but has a high macro coverage, since this group often accounts for a large

portion of total system assets. Credit can be considered at the system level (credit/GDP, system-wide growth) or at the bank level (individual bank loan growth). Each choice has implications: the system level reduces micro-noise due to reallocation of market shares, but blurs the supply/demand behavior differences at individual banks; the bank level highlights individual behavior, but requires complete and consistent data over time. With Z-score, it is important to ensure that ROA is long enough to estimate a meaningful standard deviation, while also noting that the crisis or COVID-19 period may “mutate” the sample, requiring sensitivity testing (e.g., outlier elimination, sliding windows, or winsor transformation).

Linked back to PVAR, the model allows us to answer two questions: (i) when banking stability unexpectedly increases by one standard deviation, how does credit respond over quarters — in terms of sign, magnitude, and persistence; (ii) when credit unexpectedly increases, how does the Z-score respond, statistically significantly, and over which horizons. In addition, FEVD helps quantify the relative importance of each shock in explaining the forecast variance of the other. If FEVD shows that the share of “stability shocks” in the forecast variance of credit increases over time, we have grounds to say that stability is a “hinge condition” for sustainable credit growth. Conversely, if the contribution of credit shocks to the forecast variance of the Z-score is very small over the 8–12 quarter horizon, this reinforces the argument for lags and the damping role of the macroprudential framework.

In summary, the theoretical framework and the literature review suggest a consistent picture: (1) banking stability, understood as resilience through capitalization and stable earnings, is a catalyst for sustainable credit growth; (2) credit growth, especially when prolonged and concentrated in risky assets, can sow the seeds of instability but this effect is often lagged, subject to the constraints of the prudential framework; (3) since these two forces are endogenously intertwined, a dynamic framework such as PVAR is appropriate to “capture” the response over time and quantify the relative importance of shocks; (4) in the Vietnamese institutional context, where prudential tools have been strengthened, it is reasonable to expect the “stability → credit” transmission path to be prominent in recent data, while the “credit → stability” transmission path may only be evident over longer horizons or in “boom” regimes. These conclusions frame the policy message clearly: build a stable foundation first—through capital, provisions, risk discipline, and cycle limits—and quality credit will follow; if you step on the credit accelerator before the foundation is solid enough, the cumulative risk effect will only be waiting to unfold.

3. Data and methodology

3.1. Data

This study utilizes a panel dataset comprising 29 commercial banks in Vietnam, with quarterly observations spanning the period from Q1 2008 to Q4 2024. Given that the banks in the study are publicly traded companies, their secondary data originates from disclosures on Vietnam's two official exchanges: the Ho Chi Minh City Stock Exchange (HOSE) and the Hanoi Stock Exchange (HNX). The selected sample is highly representative of the domestic banking sector, accounting for approximately 99.8% of the total assets in the Vietnamese banking system. The analysis relies exclusively on secondary data. Bank-specific financial metrics were extracted from the FiinPro database, while data for Gross Domestic Product (GDP) growth were obtained from the General Statistics Office of Vietnam (GSO).

3.2. Methodology

To investigate the dynamic interrelationships among macroeconomic conditions and bank-specific variables, this study employs a Panel Vector Autoregression (PVAR) framework. This econometric approach is selected for its capacity to effectively address the potential for endogeneity among the variables. By treating all variables as mutually endogenous within a system of equations, the PVAR model allows for a comprehensive analysis of the feedback effects between banking stability indicators and the macroeconomic environment.

Accordingly, the PVAR model is specified to examine the dynamic linkages between economic growth and a set of bank stability and performance indicators. The functional form of the model is presented as follows:

$$CRE_{it} = \mu_i + a_{l1,i} Zscore_{i,t-l} + \varepsilon_{it}$$

Where:

μ_i represents the panel-specific fixed effects.

A_l is the matrix of coefficients for lag l .

ε_{it} is the vector of error terms.

Specific Description of Variables as follows:

Table 1: Definition and Measurement of Variables

Variable	Symbol	Description	Measurement (Formula)
Credit Growth	CRE	Credit growth is the YoY percentage change in the total outstanding loans by the banking sector to the domestic economy.	$\frac{CRE}{CRE_{t-1}} - 1$
Bank Stability Proxy	Zscore	A measure of a bank's distance from insolvency; a higher value indicates greater stability.	$\frac{ROA + (Equity/Assets)}{\sigma(ROA)} - 1$

4. Results

4.1. Descriptive statistics

Table 2: Descriptive statistics

Variable Name	Obs	Mean	Std. Dev.	Min	Max
CRE	1207	0.1696	0.1673	0.0891	1.2648
Zscore	1,277	82.5010	59.8854	6.7390	538.6815

Table 2 presents the summary statistics for the variables used in this study. The dataset is an unbalanced panel, with the number of observations ranging from 1,173 to 1,278. The mean value for credit growth (**CRE**) is 0.1696, with a standard deviation of 0.1673, indicating considerable variability across the sample. The values for CRE range from a minimum of 0.0891 to a maximum of 1.2648. The **Zscore**, a measure of bank stability, has a mean of 82.5 and exhibits substantial variability, as indicated by its large standard deviation of 59.89 and a wide range from 6.74 to 538.68. To calculate the standard deviation of the Z-score, we take data with a deviation of 3 quarters in the past. The value of 538.68 is actually an outlier, because the data of NVB bank has a very small standard deviation. However, this data was still kepted, with the aim of reflecting the reality as honestly as possible.

4.2. Cross-Sectional Dependence Test

Table 3: Cross-Sectional Dependence Test

Variable	Pesaran CD Test	CIPS Unit Root Test (Levels)	CIPS Unit Root Test (1st Diff.)	Conclusion
	Statistic (p-value)	Statistic (p-value)	Statistic (p-value)	

CRE	0.000	0.000	...	I(0)
Zscore	0.000	0.669	0.000	I(1)

Note: CIPS test null hypothesis is that all series have a unit root. A p-value < 0.05 indicates rejection of the null, implying stationarity.

Prior to model estimation, it is imperative to examine the econometric properties of the panel data. We first test for the presence of cross-sectional dependence (CSD), which is common in banking panels due to systemic shocks and interconnections. The results of the Pesaran (2004) CD test are presented in Table 3. For all variables (CRE, Zscore), the null hypothesis of cross-sectional independence is strongly rejected at the 1% significance level (p-value = 0.000). This confirmation of CSD necessitates the use of second-generation panel data techniques that account for such dependence.

Given the presence of CSD, we employ the Cross-sectionally Augmented Im-Pesaran-Shin (CIPS) panel unit root test. The results in Table 3 show that for credit growth (CRE), the null hypothesis of a unit root is rejected at the 1% level. Therefore, these variables are stationary in their levels, denoted as I(0). Conversely, the CIPS test fails to reject the null hypothesis for the Z-score (Zscore) at conventional significance levels, indicating they are non-stationary. After taking the first difference, the test is reapplied to this variable. The results show that the null hypothesis is strongly rejected for the first-differenced series of Zscore (p-value = 0.000). This confirms that Zscore is integrated of order one, denoted as I(1). The mixed order of integration among the variables further justifies the selection of the Panel VAR methodology for the main analysis.

4.3. PVAR Lag Order Selection

Table 4: PVAR lag order selection

Lag Order (p)	CD	J-Statistic	p-value (J)	MAIC	MBIC	MQIC
1	.9705196	129.0762	6.32e-15	-44.65141	73.07621	26.8603
2	.955981	62.59304	.0000273	-86.31635	14.59304	-25.0206
3	.9241524	46.22603	.0007504	-77.86513	6.226026	-26.78534
4	.9625736	25.3807	.0633891	-73.89222	-6.619298	-33.02839
5	.8246827	5.282401	.9478753	-69.17229	-18.7176	-38.52442
6	.6383426	3.397983	.9069614	-46.23848	-12.60202	-25.80656
7	.5285584	2.35734	.6703499	-22.46089	-5.64266	-12.24493

Note: Asterisk (*) denotes the optimal lag selected by each criterion. CD is the overall coefficient of determination. J-statistic is Hansen's test of overidentifying restrictions.*

The determination of the appropriate lag length is a critical preliminary step in the estimation of the Panel Vector Autoregression (PVAR) model. The optimal lag was selected based on the model selection criteria proposed by Andrews and Lu (2001), which are adapted for GMM estimation. These criteria include the Moment-based Bayesian Information Criterion (MBIC), Moment-based Akaike Information Criterion (MAIC), and Moment-based Hannan-Quinn Information Criterion (MQIC). Additionally, Hansen's J statistic is used to test the validity of the overidentifying restrictions.

The results of the lag selection process, for a maximum of 7 lags, are presented in the output table. The **MAIC** and **MQIC** are minimized at **lag 5**, with values of -18.7176 and -38.52442, respectively. The **MBIC** reaches its minimum value at **lag 2** (-86.31635). As two of the three criteria (MAIC and MQIC) suggest a more parsimonious model, the optimal lag length of **5** is selected for the subsequent analysis. This choice is further

supported by the Hansen J-statistic p-value of 0.9489 at lag 5, which indicating the validity of the model at this lag length.

4.4. PVAR Estimation Results

Given that the individual coefficients in a Panel Vector Autoregression (PVAR) model are difficult to interpret directly in economic terms, this section focuses on post-estimation analyses to elucidate the dynamic relationships among the variables. The analysis includes model stability diagnostics, Impulse Response Functions (IRF), Forecast Error Variance Decomposition (FEVD), and Granger causality tests.

4.4.1. Model Validity and Stability

To ensure the reliability of the Panel VAR model, a series of diagnostic tests for each equation were conducted to validate the GMM estimation. The results, presented in the table, confirm that the model is well-specified.

Table 5: Diagnostic Test Results

Test	(1) CRE	(2) Zscore
Arellano-Bond Autocorrelation Test		
AR(1) (p-value)	0.000	0.010
AR(2) (p-value)	0.237	0.112
Hansen Test for Instruments		
Hansen Test (p-value)	1.000	1.000

First, the **Arellano-Bond test for serial correlation** was performed. The critical test for second-order serial correlation (AR(2)) yields high p-values across all two model equations (ranging from 0.112 to 0.237). The failure to reject the null hypothesis of no second-order correlation confirms that the model is dynamically complete and does not suffer from misspecification.

Second, the **Hansen test of overidentifying restrictions** was used to assess the overall validity of the instruments. The test results provide a p-value of **1.000** for all equations, indicating that the null hypothesis of valid instruments cannot be rejected. This provides strong evidence that the instruments are exogenous and correctly exclude

Table 6: Eigenvalue Stability Condition Results

Real	Imaginary	Modulus
-.0248545	.7267093	.7271342
-.0248545	-.7267093	.7271342
-.7185181	0	.7185181
.5391019	.3542612	.6450829
.5391019	-.3542612	.6450829
.6306165	0	.6306165
-.493578	0	.493578
.0350277	.2863601	.2884945
.0350277	-.2863601	.2884945
.2859929	0	.2859929

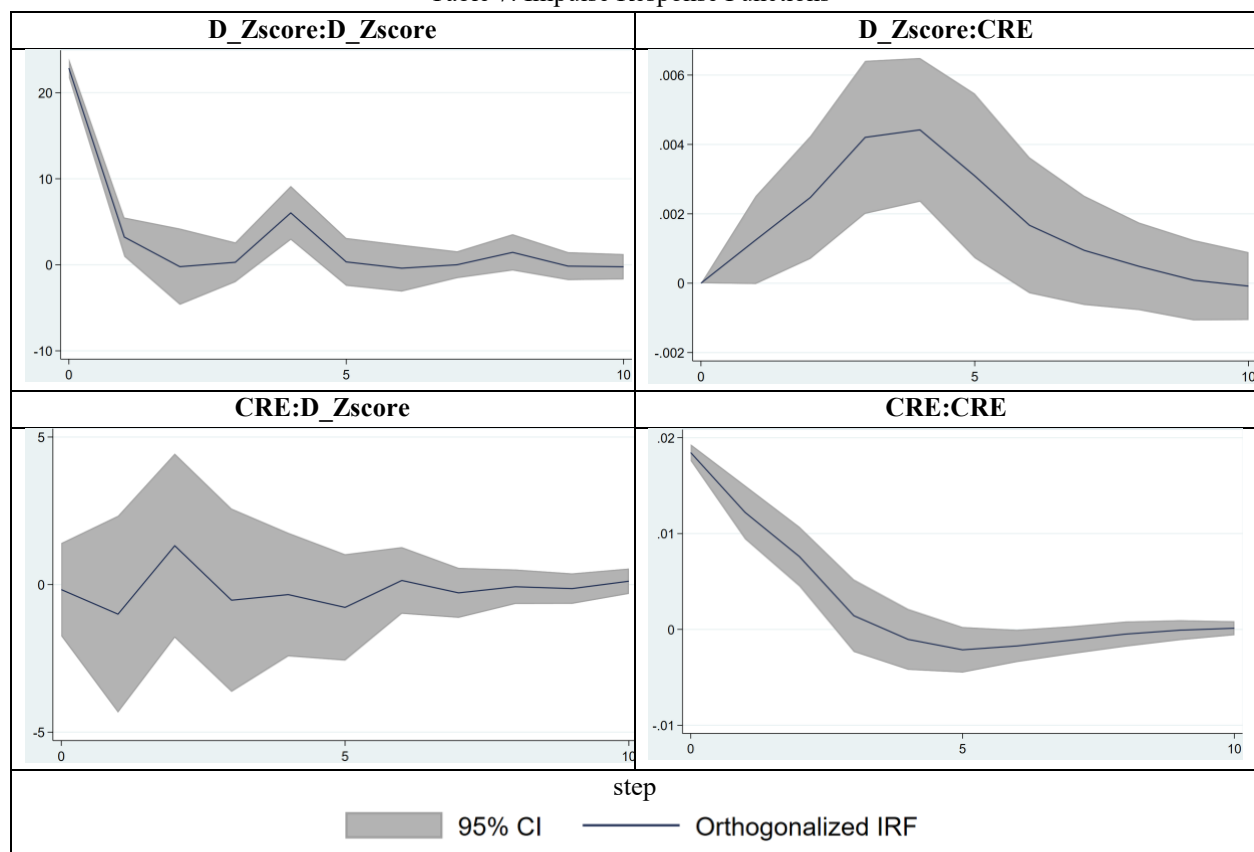
All the eigenvalues lie inside the unit circle.
pVAR satisfies stability condition.

Next, the stability of the PVAR model, a critical precondition for meaningful IRF and FEVD analysis, was assessed. The results confirm that all eigenvalues of the companion matrix lie inside the unit circle, meaning their modulus less than one. This satisfies the stability condition, ensuring that the effects of any shocks are transitory and will dissipate over time, allowing for robust dynamic analysis.

4.4.2. Impulse Response Functions (IRF)

Impulse Response Functions (IRFs) are used to trace the effects of a one-standard-deviation shock from one variable onto others in the system over a 10-quarter horizon.

Table 7: Impulse Response Functions



A positive shock to bank stability (D_Zscore) causes a positive and statistically significant increase in credit growth (CRE). This positive effect is persistent, lasting for the entire 10-period forecast horizon. In contrast, shocks from CRE has insignificant impact on bank stability. The confidence interval for this response is wide, range from -5 to +5, it means we cannot be statistically certain that the true effect is different from zero. For a 95% confidence interval, the response of Zscore to an impulse from CRE has a negative effect at first, then it strikes upward in shortterm to neutralize the effect.

4.4.3. Forecast Error Variance Decomposition (FEVD)

The Forecast Error Variance Decomposition (FEVD) reveals the proportion of the forecast error variance of each variable that can be attributed to shocks from other variables.

Table 8: Forecast Error Variance Decomposition Data

Response Variable	Forecast Horizon	CRE	D_Zscore
CRE	0	0.000000	0.000000
	1	1.000000	0.000000
	2	0.996844	0.003156
	3	0.986179	0.013821
	4	0.955878	0.044122
	5	0.924570	0.075430
	6	0.910599	0.089401
	7	0.906906	0.093094
	8	0.905780	0.094220
	9	0.905470	0.094530
	10	0.905460	0.094540
D_Zscore	0	0.000000	0.000000
	1	0.000055	0.999945
	2	0.001938	0.998062
	3	0.005170	0.994830
	4	0.005692	0.994308
	5	0.005530	0.994470
	6	0.006567	0.993433
	7	0.006599	0.993401
	8	0.006735	0.993265
	9	0.006720	0.993280
	10	0.006752	0.993248

The Forecast-Error Variance Decomposition (FEVD) indicates that the relationship appears to be a **one-way street**: bank stability shocks have a modest impact on credit growth, but credit growth shocks have very little effect on bank stability. The results for bank stability are very clear. It is almost completely endogenous, meaning it's self-driven. Even after 10 periods, over 99% of its forecast variance is explained by its own past shocks. The influence of credit growth on bank stability is negligible (less than 1%). Credit growth is also largely explained by its own history, but it's more open to outside influence. Over the 10-period horizon, the influence of D_Zscore shocks grows steadily to account for about 9.5% of the variance in credit growth. The remaining 90.5% comes from its own shocks.

4.4.4. Granger Causality Tests

Table 9: Panel VAR-Granger Causality Wald Test

Equation (Dependent)	Excluded (Cause)	chi2	df	Prob > chi2
CRE	D_Zscore	21.537	5	0.001
	ALL	21.537	5	0.001

D_Zscore	CRE	6.719	5	0.242
	ALL	6.719	5	0.242

Based on the Granger causality test, the results indicate a unidirectional causal relationship running from bank stability (D_Zscore) to credit growth (CRE). The test shows that past values of bank stability significantly help predict future values of credit growth, with the result being statistically significant at the 1% level ($p = 0.001$). Conversely, the test found no evidence of a causal relationship in the opposite direction; the influence of past credit growth on bank stability was not statistically significant ($p = 0.242$).

5. Discussion

This discussion summarizes and interprets the empirical results of the study on the dynamic relationship between credit growth (CRE) and bank stability (Z-score) in a sample of 29 Vietnamese commercial banks during the period Q1/2008–Q4/2024, and places them in the institutional and financial cycle context of Vietnam. The main results are threefold: (i) the impulse response functions (IRFs) show that a shock to bank stability increases credit with persistence over multiple quarters; (ii) the short- to medium-term credit growth shock does not produce a statistically significant response to Z-score; and (iii) the forecast error variance decomposition (FEVD) shows asymmetry in that the variation of Z-score is almost determined by its own past shocks, while the variation of credit is increasingly explained by the “stabilization” shock when the forecast horizon is extended (reaching approximately 9–10% in the 10th quarter). Granger causality tests clarify this picture: stability “causes” credit ($p \approx 0.001$), while credit does not “cause” stability over the considered period and model configuration ($p \approx 0.24$). Below, we discuss in depth the economic mechanisms behind the results, their connection to the context and policies in Vietnam, assess the reliability of the estimates, the limitations of the study, and further suggestions.

First, the interpretation of the transmission channel from “stability $\rightarrow$ credit” is quite intuitive within the framework of a financial amplifier: a high Z-score implies a favorable combination of the three pillars — positive profit margins, adequate capitalization, and low profit volatility — thereby reducing the cost of external financing, easing capital and leverage constraints, and increasing risk tolerance. In practice, a “positive stability” shock can come from improved ROA due to operational efficiency, increased equity capital, or better risk management that reduces profit volatility. In this case, the bank has room to expand its loan portfolio without sacrificing too much of its safety margin; on the other hand, the market also responds by lowering the “risk premium” in the structure of bank deposit and bond interest rates, lowering the cost of capital. IRF accordingly recorded that credit growth increased and was maintained for many quarters, reflecting the typical “slowing down” of balance sheet adjustment: from improving stability to deciding on credit growth limits and plans, and then disbursing into the economy, all need time to spread.

In contrast, the “credit $\rightarrow$ stability” channel does not show significant short-to-medium term feedbacks, a result that is both consistent with cyclical risk theory and consistent with Vietnam’s recent macroprudential context. Rapid credit growth, in principle, sows future risks through easing credit standards, accumulation of maturity mismatches, and leverage in the corporate/residential sectors. However, such effects often require a lag to “crystallize” on financial statements, through the emergence of bad debts, increased provisioning expenses, or narrowing of net interest margins during the cyclical reversal phase. When the observation frequency is quarterly and the stability measure is the Z-score — a composite index — the short-term impact of a credit shock is usually small and easily “masked” by favorable capital and profit buffers. The lag becomes more evident when regulators apply macroprudential “safety valves”: limiting the risk coefficient for real estate/corporate loans, regulating the ratio of short-term capital for medium- and long-term loans, raising capital requirements according to Basel II/III, tightening debt classification and provisioning, along with centralized monitoring of credit and system liquidity. In other words, the more “shock absorbers” there are, the less credit translates into measurable fluctuations on the Z-score over an 8–10 quarter horizon, although medium-term risks still exist if credit remains high and concentrated in risky segments.

The “asymmetry” in FEVD reinforces this interpretation: the future volatility of Z-score is almost determined by the “history of Z-score” (autogenous), while the future volatility of credit, in addition to its own inertia, receives an “increasing contribution” from the stability shock. This is, in fact, the hallmark of a dynamic structure in which “stability” plays the role of background conditions, while “credit” is a behavioral variable sensitive to changes in background conditions. The evidence of one-way causality makes the message even sharper: in the Vietnamese data of the study period, stability is the driving force for credit forecasts, but not the other way around at the frequency/time horizon considered. The policy implications of this message are clear: instead of “pushing” credit with administrative measures or hastily loosening safety barriers, the focus should be on strengthening balance sheet resilience and risk discipline; quality credit will follow as a natural consequence.

Putting the results into the context of Vietnam, the period 2008–2024 is the period when the banking system underwent deep restructuring (after the 2008–2012 shock), implemented Basel II (capital standardization, ICAAP, pillars 2–3), raised debt/provision classification standards, faced the COVID-19 shock and then recovered, in parallel with the boom and adjustment of real estate credit and corporate bonds. This series of institutional adjustments follows the philosophy of “building a cyclical safety cushion”: increasing endurance in favorable periods, intervening in risk allocation orientation (higher risk coefficients for hot segments), and setting up a liquidity safety net to reduce the risk of contagion. In that context, it is not surprising that the IRF recorded “credit stability” while “credit has not yet caused instability” in the short term. However, this is not a suggestion for waves of hot credit growth; On the contrary, it reminds that maintaining “safety valves” is a necessary condition to ensure that credit expansion does not come at the expense of a progressive deterioration of the Z-score over the longer horizon.

One notable empirical issue is the nature of the robustness measure. The Z-score, which combines three components—profitability, capitalization, and earnings volatility—should be sensitive to short-term fluctuations in ROA and to changes in accounting recognition (e.g., period-wise provision accruals, provision reversals, or increases/decreases in non-credit activities). In some contexts, a credit growth shock may be accompanied by a short-term increase in interest income, causing a temporary improvement in the Z-score and unintentionally “masking” the risk accumulation in asset quality. In this case, the absence of an immediate negative response of the Z-score to a credit shock does not mean that credit is harmless; it only reflects the lag in recording risk in the books and the buffering role of earnings. Therefore, we believe that the interpretation of the results could be better if enriched with additional indicators (NPL, CAR, LCR/NSFR, risky loan ratio, etc.) in subsequent studies. Another extension that has a cyclical economics bent is to test for nonlinearity and regime change. In practice, the system can operate in two “regimes”: normal and boom. When credit/GDP exceeds a threshold, or when the rate of systemic credit growth persists above a threshold for several quarters, the “credit → stability” transmission path may become more pronounced (negative Z-score response), while the “stability → credit” transmission path may increase in slope during the boom phase. TVAR, threshold PVAR, or quantitative PVAR models are suitable tools to test this hypothesis. In addition, grouping banks by size, ownership, capitalization, income diversification (credit/non-credit) or concentration in real estate/consumption will help to examine the heterogeneity in transmission. This is particularly useful for “targeted” policy recommendations: thinly capitalized, high-risk segments may require a more aggressive dose of prudential instruments than healthy ones.

6. Conclusion and implications

Overall, the research results send consistent signals for “coordinating” the credit growth and system stability targets. First, the policy priority should be placed on improving the quality of stability: increasing capital (including capital quality), maintaining cross-cyclical provisioning discipline, strengthening risk management, and controlling the focus on high-risk segments. Second, maintaining and refining macroprudential tools according to the cycle: when conditions are favorable, use tools to build buffers (e.g. dynamic provisioning-like mechanisms, countercyclical buffer triggering indicators if/when applicable), and when conditions are bad, use buffers to “relieve” pressure while maintaining essential credit flows to the real sector. Third, shift the focus from “credit quantity” to “credit quality”: encourage credit to the manufacturing-export sector, supporting industries, technological innovation, and appropriate risk discounting for sensitive segments such as real estate, unsecured consumption. Fourth, developing the capital market to reduce the monopoly role of banks in medium-

and long-term financing; the complementarity of the corporate bond/equity market along with good transparency standards and market discipline will blur the amplification loop between banks-real estate-collateral.

At the micro-management level, banks can draw some lessons. First, investing in “stable quality”—as reflected in Tier 1 capital, core earnings quality, quantitative risk appetite framework, and PD/LGD measurement capabilities according to IFRS 9—is not just a compliance requirement but a lever for sustainable credit growth. Second, building an early warning system by category to detect “silent” loosening of credit standards during periods of high competition; this helps avoid the accumulation of invisible risks that Z-scores have not yet reflected in a timely manner. Third, managing capital and maturity according to the structural liquidity structure (LCR/NSFR) to limit the risk of credit growth turning into liquidity stress when the cycle reverses. Taken together, our empirical evidence leads to the central conclusion: in the context of Vietnam in the period 2008–2024, banking stability is a “hinging condition” for promoting sustainable credit growth, while the adverse effect from credit on stability is not evident in the short–medium term horizon when the macroprudential framework operates effectively. The policy message is therefore “order of priority”: build a foundation of stability first—through capital, provisions, risk management, and prudential instruments—and quality credit will follow; boosting credit without strengthening the foundation can only temporarily bring surface growth, but in return accumulate risks for the next cycle. This study, by modeling the endogenous dynamics between CRE and Z-score in PVAR, contributes a Vietnamese-based evidence to the “credit-generating stability” narrative and suggests a further research agenda on nonlinearities, bank differentiation, and the role of cyclical prudential instruments in moderating this relationship.

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