Journal of Accounting, Business and Finance Research
Vol. 20, No. 2, pp. 31-41, 2025
DOI: 10.55217/102.v20i2.996

The impact of GDP growth on banking stability in Vietnam: A PVAR model analysis

Nguyen Thanh Trung

School of Banking and Finance, National Economics University, Vietnam.
Email: thanhtrung@neu.edu.vn

Abstract

This study investigates the dynamic interplay between real economic activity and banking system resilience in Vietnam using a quarterly panel of 29 commercial banks from Q1/2008 to Q4/2024. Employing a Panel Vector Autoregression (PVAR) framework, we trace how unexpected movements in GDP growth propagate to a standard measure of bank soundness—the Z-score, which captures a bank's distance to insolvency by combining profitability, capitalization, and earnings volatility. The results indicate statistically significant bidirectional Granger causality between GDP growth and the Z-score, implying a feedback loop in which stronger macroeconomic conditions bolster bank stability, and a more stable banking sector, in turn, supports subsequent economic performance. Impulse-response functions show that a positive GDP growth shock raises banking stability in the short run, with the effect peaking around the third to fourth quarter before gradually dissipating. Interestingly, conventional income- and credit-risk channels—net interest margin (NIM), non-interest income (NII), and non-performing loans (NPL)—do not exhibit significant direct responses to GDP growth shocks. However, when we examine how NIM relates to the Z-score, the evidence suggests that the dominant transmission mechanism may run through monetary policy and bank-internal balance-sheet features such as capitalization and the stability of earnings rather than through margin widening, fee income shifts, or immediate improvements in asset quality. Taken together, these findings underscore the importance of countercyclical buffers and prudent capital management to sustain resilience over the business cycle. Policy implications include reinforcing capital and liquidity requirements that tighten in booms and relax in downturns, maintaining clear monetary policy communication to stabilize funding conditions, and encouraging diversification strategies that reduce earnings volatility without incentivizing excessive risk-taking. Such measures can help lock in the stabilization benefits of growth while limiting procyclical vulnerabilities in Vietnam's banking system.

Keywords:
Banking stability
Financial development
GDP growth
Integrated risks
Vector autoregressive (VAR) model
Z-score.

Copyright:
© 2025 by the author. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/)

Publisher:
Scientific Publishing Institute

Received: *23 August 2025*
Revised: *26 August 2025*
Accepted: *11 September 2025*
Published: *15 September 2025*

Funding: This study received no specific financial support.
Institutional Review Board Statement: Not applicable.
Transparency: The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Competing Interests: The author declares that there are no conflicts of interests regarding the publication of this paper.

1. Introduction

In recent decades, the relationship between economic growth and financial stability, particularly banking stability, has become a popular discussion in macroeconomics and banking finance. Banks serve as key financial intermediaries, ensuring the efficient allocation of capital from savers to investors, a crucial function in developing and emerging economies. Therefore, the stability of the banking system is a prerequisite for maintaining sustainable growth, while GDP growth is a determinant of the scale, speed, and structure of banking activities.

However, this relationship is not always straightforward. A strongly growing economy can provide a solid foundation for banks but may also conceal risks of instability if growing process is accompanied by financial imbalances. Major financial crises, as indicated, from the Great Depression of the 1930s to the 2008 global financial crisis, have shown that periods of strong GDP growth often precede crises and are associated with excessive credit expansion, increased financial leverage, and asset price bubbles. Consequently, analyzing the transmission mechanisms through which GDP growth affects banking stability is essential for designing macroprudential policies in order to prevent systemic risks.

This study is conducted in the context of Vietnam, a nation striving for high GDP growth to escape the middle-income trap before it moment of population aging. This pursuit of high growth may exposes the country to financial pressures, such as rising asset prices, moral hazard risks, excessive optimism, and a decline in the quality of bank balance sheets. Our research goal is assessing the impact of GDP growth on banking stability within Vietnam's specific context.

This study primarily seeks to answer the following questions: How does GDP growth affect the stability of the banking system in Vietnam, and which transmission channel plays a dominant role in this relationship?

In order to find out the answer these questions, the study employs a quantitative approach to evaluate the impact of GDP growth on banking stability in Vietnam. We utilize a Panel Vector Autoregressive (PVAR) model to analyze the dynamic relationships among macroeconomic and microeconomic variables over time.

- The main variables included in the model are:
- GDP growth (gGDP): The macroeconomic variable representing economic growth.
- Z-score: The microeconomic variable representing banking system stability.
- NIM, NII, NPL: Microeconomic variables representing potential transmission channels.
- The PVAR model allows us to analyze Impulse Response Functions (IRFs) and Variance Decompositions (VDs) to:
- Determine the response of the Z-score to a shock in GDP growth.
- Analyze the transmission channels (NIM, NII, NPL) through which GDP growth affects the Z-score.
- Measure the contribution of each variable to the fluctuations of other variables.

2 Literature Review

2.1. Definition of Banking Stability

Banking stability can be understood, in simple terms, as a state in which banks continue to meet their financial obligations, maintain essential services for the economy, and avoid causing major disruptions to the system. Following Crockett (1997) the hallmark of instability is “financial stress”: when a bank can no longer meet its obligations on its own and must rely on external support. In practice, banks in such distress often resort to selling assets at depressed prices, recognize losses, and thereby inflict serious damage on larger institutions—and even push smaller ones toward bankruptcy. From a market perspective, stability is also associated with avoiding sharp price swings that produce system-wide harm. Market risk factors influence bank performance in two ways: directly by altering the market value of on-balance-sheet assets, and indirectly by eroding borrowers' credit quality.

The European Central Bank (2005) does not define “banking stability” explicitly, but addresses it through the broader concept of financial stability: a financial system that can provide continuous support to the economy while helping to sustain growth. This view builds on Borio (2003) who emphasizes two complementary pillars: a micro-prudential perspective that measures and controls risks at the institutional level to lower the probability of individual failures, and a macro-prudential perspective that looks at the system as a whole to curb procyclicality and crisis spillovers.

On the empirical side, the International Monetary Fund (2002)—a consolidated set of indicators used to monitor the health and resilience of financial institutions and markets, as well as related corporate and household sectors. FSIs include aggregate information on deposit-taking institutions and on the markets in which they operate. Beyond such composites, many studies rely on credit-risk measures—such as the nonperforming loan (NPL) ratio or loan-loss provisions to total loans—as especially sensitive indicators of financial stability. Wanke, Adhikari, and Shah (2016) show that the CAMELS framework (capital adequacy, asset quality, management, earnings, liquidity, and sensitivity to market risk) is effective for early warning of financial distress in banks.

A more general gauge, popularized by the World Bank (2005) is the Z-score. It compares a banking system's buffers—profitability and capitalization—to the volatility of those profits and is commonly computed as Zscore $=\frac{ROA+\frac{Equity}{ROA}}{\sigma_{ROA}}$.

Here, σ(ROA) is calculated at an annual frequency using at least five bank-level observations; results are not reported for years in which a country has fewer than three banks. The ROA, equity, and asset figures are aggregated at the country level from unconsolidated bank data (e.g., Bankscope/Orbis). Intuitively, a higher Z-score implies a greater "distance to insolvency" and thus a more stable bank. In empirical research, the Z-score is often the primary measure of stability for commercial banking systems, supplemented by stress indicators such as the NPL ratio and provisioning measures to capture both credit risk and earnings volatility.

2.2. Impact of GDP Growth on Banking Stability

A rapid, sustained GDP growth can unsettle banks through several interlinked—and often indirect—channels that wax and wane with the business and financial cycle. The relationship runs both ways: banks benefit from expansion, yet the very forces that lift profits can also magnify risk. In long upswings, transmission mechanisms reshape incentives inside banks and across markets, gradually loosening constraints until a reversal exposes accumulated fragilities.

First, stronger growth typically lifts loan demand from households and firms. To capture volume and margins, banks expand credit and, under competitive pressure, ease underwriting. Credit then outpaces GDP, setting up a boom-bust dynamic: when growth slows, borrower cash flows weaken, defaults rise, and banks face a credit recession. A rapid run-up in credit during expansions is among the most reliable precursors of later financial distress (Schularick & Taylor, 2012).

Second, expansions usually coincide with rising real estate and equity prices. As collateral values climb, measured borrower leverage looks safer, encouraging still more lending. This feedback loop—credit fueling asset prices and asset prices validating more credit—raises the system's sensitivity to a price correction. When asset prices fall, collateral values drop, risk weights and required provisions increase, and capital ratios compress, forcing banks to deleverage. Joint surges in credit and asset prices materially elevate the probability of a banking crisis within the next few years (Borio & Lowe, 2002).

Third, long good times breed optimism. Risk models calibrated on benign data understate tail risk; qualitative controls erode as lenders reach into previously off-limits segments. Competitive dynamics amplify this drift, producing moral hazard and a tilt toward riskier, often real-estate-backed, exposures. Liquidity cushions are pared back on the assumption of stable deposits and easy wholesale funding. High growth coupled with thinning capital and liquidity buffers is a classic warning sign of system vulnerability (International Monetary Fund (IMF), 2011).

Fourth, policy settings often reinforce these cycles. Pro-growth strategies commonly feature accommodative monetary policy and liberalized capital flows. Low interest rates compress funding costs and spur leverage, while foreign inflows can fuel domestic credit booms and foreign-currency borrowing. When conditions turn, debt service burdens jump, nonperforming loans rise, and currency mismatches pressure balance sheets. Crucially, the financial cycle tends to be stronger and longer than the output cycle, so risks can keep building even after GDP growth has peaked (Claessens, Kose, & Terrones, 2011). Historically, deep recessions and systemic crises have followed periods of rapid growth entangled with credit and asset-price bubbles (Reinhart & Rogoff, 2009).

In sum, growth is not the enemy of banking stability—but unguarded, credit- and asset-price-intensive growth is. The policy antidote is to lean against the cycle: maintain borrower-based limits (e.g., LTV/DTI), build countercyclical capital and liquidity buffers in booms, price FX and maturity mismatches appropriately, and enforce rigorous, through-the-cycle underwriting. These measures let banks share in the upside of expansion without sowing the seeds of the next bust.

2.3. Transmissions Channels from GDP Growth to Banking Stability

To measure the level of bank stability, Z-score is considered as an effective measure. This indicator can reflect the level of asset volatility of the bank in correlation with the profit from business activities as well as the capital buffer that the bank adds during the process of increasing assets (shown through the size of ROE or CAR). However, as presented above, the financial cycle is often longer than the GDP growth cycle (Claessens et al., 2011) the assessment based on Z-score alone shows the relationship between GDP growth and bank stability, but does not reflect which transmission channel will play a key role in this relationship.

In this study, we look at the indicators that are considered to be important in reflecting the quality of a bank's operations, including NIM, NII and NPL. We attempt to explain the relationship between GDP growth and these indicators, combined with the final goal of Z-score, to find out which transmission channel is the main one determining the impact of GDP on banking stability in Vietnam.

On NIM and NII: The classic study by Demirgüç-Kunt and Huizinga (1999) shows that macroeconomic conditions (including growth/cycle, inflation, financial structure) explain the difference in NIM and profitability across countries. Thus, an increase in GDP will affect NIM, and this effect may be positive because NIM can increase due to increased credit demand. This empirical evidence is collected on 80 countries over the period from 1988 to 1995.

However, if high GDP growth is associated with persistently low interest rates, cross-country evidence confirms that low interest rates lead to lower NIMs. This may lead to a reduction in NIMs as credit volumes increase (Fed IFDP Notes 2016; CEPR VoxEU; RBA 2023; CESifo WP). This could be due to banks reducing lending rates more than their funding costs, or sacrificing some core revenue as non-interest income tends to grow faster.

In emerging markets, according to the study of the Bank for International Settlements (Kohlscheen, Murcia Pabón, & Contreras, 2018) GDP growth is negatively correlated with NII. According to these authors, in bad times, banks often try to increase profits by increasing other sources of income, such as fees and commissions. GDP growth is also negatively related to NIM. This result is also consistent with some previous studies (Demirgüç-Kunt & Huizinga, 1999). In the context of good economic growth, when credit demand is strong, banks tend to reduce net interest income to increase market share. Moreover, the highly volatile economic cycle in these emerging countries, which can cause credit to be broken frequently, also explains the above conclusion.

On NPL: The research results of Beck, Jakubík, and Piloiu (2013) show that GDP growth increases NPL in the short term, then reduces NPL with a lag of 1 year. Other factors such as exchange rate, lending interest rate, stock price also have important impacts. In the context of European countries, this study confirms the leading role of GDP growth on NPL in the past few decades. In addition, exchange rate depreciation is also the main cause of the increase in NPL in countries with high levels of foreign currency lending to unprotected borrowers.

From a systemic risk perspective, Schularick and Taylor (2012) found that credit booms and rising asset prices are the causes of subsequent crises. Using data from 14 countries over the period from 1870 to 2008, the authors concluded that strong credit growth is a predictor of future financial crises, while policymakers tend to ignore this risk. This conclusion supports the view that bad debts increase sharply during recessions, usually after a period of GDP growth accompanied by strong credit growth.

Regarding Z-score: Gabrielsson (2023) study on 24 European countries from 2006 to 2020 shows a positive relationship between economic growth and banking stability, if banking stability is measured by the NPL ratio. However, this relationship is not statistically significant when applied to Z-score. Čihák and Hesse (2010) study confirms that Z-score is a measure that reflects the distance to bankruptcy of banks and is widely used in comparing banking stability; creating a basis for using Z-score in analyzing the relationship between GDP growth and banking stability.

3. Methodology and Data

In this study, we tends to utilize 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 are publicly traded companies, their data are collected 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).

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:

$$Y_{it} = \mu_i + \sum_{l=1}^{p}(a_{l1}\, Zscore_{i,t-l} + a_{l1,i}NPL_{i,t-l} + a_{l1,i}NII_{i,t-l} + a_{l1,i}NIM_{i,t-l}) + \varepsilon_{it} \quad (1)$$

Where:

Y_{it} is the vector of endogenous variables at time t for panel i, $y_{it} = \begin{bmatrix} gGDP_{it} \\ Zscore_{it} \\ NIM_{it} \\ NPL_{it} \\ NII_{it} \end{bmatrix}$

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)
Gross domestic product growth	gGDP	The quarterly percentage change in real GDP, proxying for the state of the macroeconomy.	$\frac{GDP_t}{GDP_{t-1}} - 1$
Bank stability proxy	Zscore	A measure of a bank's distance from insolvency; a higher value indicates greater stability.	$\frac{\text{ROA+(Equity/Assets)}}{\sigma(\text{ROA})} - 1$
Net interest margin	NIM	A ratio indicating the profitability of a bank's core lending and funding activities.	$\frac{\text{Interest Income} - \text{Interest Expense}}{\text{Average Earning}}$
Non-interest income ratio	NII	The proportion of a bank's income derived from non-core, fee-based activities.	$\frac{\text{Non Interest Income}}{\text{Total Operating Income}}$
Non-performing loan ratio	NPL	The proportion of a bank's loan portfolio that is subject to default, indicating credit risk.	$\frac{\text{Non Performing Loans}}{\text{Total } Loans}$

Table 2. Decriptive statistics.

Variable Name	Obs.	Mean	Std. dev.	Min.	Max.
gGDP	1,278	0.1395	0.1150	-0.0335	0.6120
Zscore	1,277	82.5010	59.8854	6.7390	538.6815
NPL	1,173	0.0242	0.0256	0.001	0.3593
NIM	1,278	0.0329	0.0144	-0.0088	0.1566
NII_P	1,261	0.0015	0.0017	-0.0078	0.0230

Source: Author's synthesis (Based on data collected).

4. Data

4.1. Descriptive Statistics

Table 2 presents the summary statistics for the variables used in this study. The dataset is a slightly unbalanced panel, with 1,278 quarterly observations for most variables, while the Non-Performing Loan ratio (NPL) and the Non-Interest Income ratio (NII) have 1,173 and 1,261 observations, respectively.

The average quarterly GDP growth (gGDP) is 13.95%, with a standard deviation of 11.50%. The highest value was obtained in the first quarter of 2021 is 61% - possibly the recovery period in the Covid19 pandemic, while the lowest value was approximately -3% in the second quarter 2019.

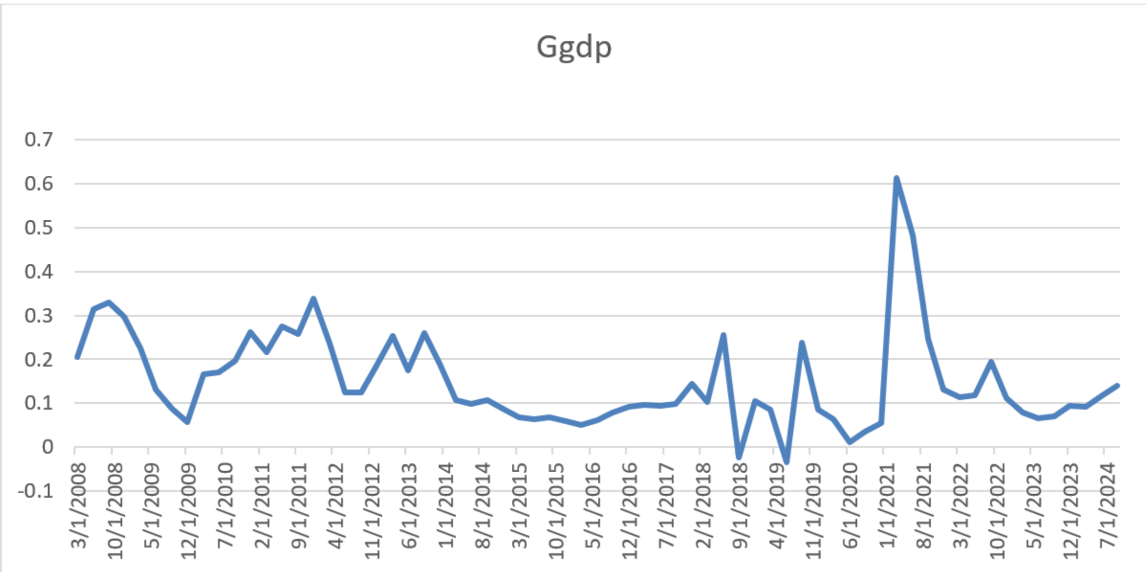


Figure 1. Vietnamese GDP growth chart – quarterly observation.

Source: Author's synthesis (Based on data collected).

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 keeped, with the aim of reflecting the reality as honestly as possible.

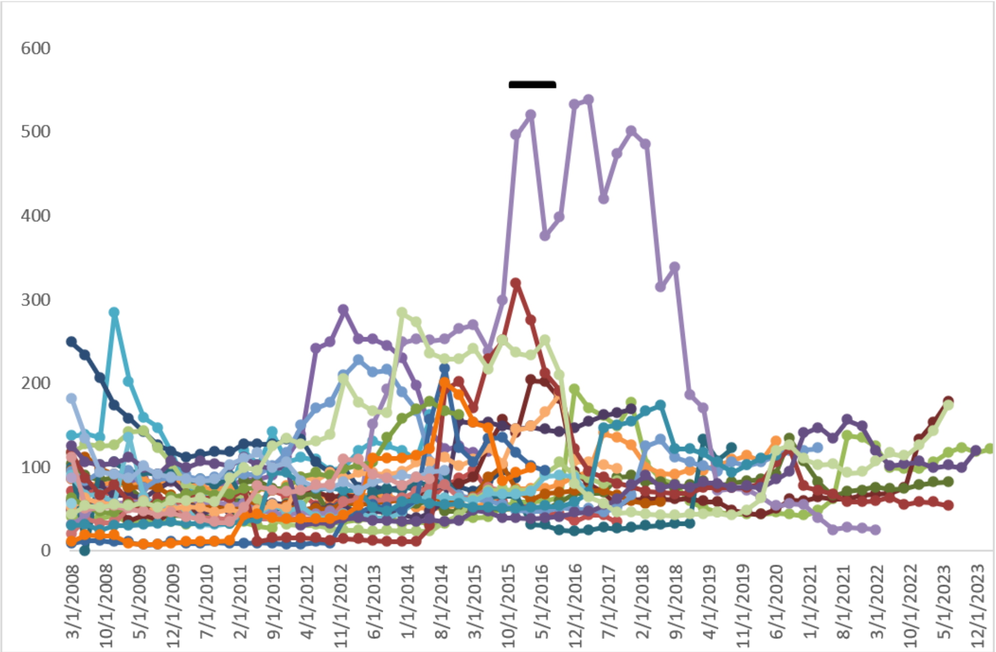


Figure 2. Vietnamese banking stability chart (Z-score) – Quarterly observation.
Source: Author's synthesis (Based on data collected).

On average, the NPL is low at 2.42%, with a standard deviation of 2.56%. The Net Interest Margin (NIM) has a mean of 3.29% and a standard deviation of 1.44%. Finally, the Non-Interest Income ratio (NII) is relatively small, with a mean of 0.15%.

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)	
gGDP	0.000	0.000	…	I(0)
Zscore	0.000	0.669	0.000	I(1)
NPL	0.000	0.416	0.000	I(1)
NII	0.000	0.000	...	I(0)
NIM	0.000	0.000	…	I(0)

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.
Source: Author's synthesis (Results obtained using Stata17).

5. Results and Discussions

5.1. Cross-Sectional Dependence Test

A preliminary diagnostic test was conducted to assess the presence of cross-sectional dependence (CSD) across the panel units for each variable in the model. The results, derived from the Pesaran (2004) CD test, are presented in the table. The null hypothesis of this test is that the variables are cross-sectionally independent.

The test results provide strong evidence to reject the null hypothesis for all variables. The CD test statistics are all statistically significant at the 1% level: Zscore (59.52, p=0.000), gGDP (164.93, p=0.000), NPL (-5.69, p=0.000), NII (49.38, p=0.000), and NIM (20.97, p=0.000). The statistical significance across all variables indicates the presence of strong cross-sectional dependence in the data. This finding implies that shocks to an individual bank are likely contemporaneously correlated with shocks to other banks within the sample, a critical consideration for subsequent model estimation.

Table 4. PVAR lag order selection.

Lag Order (p)	CD	J-Statistic	p-value (J)	MAIC	MBIC	MQIC
1	9.955.364	1.980.016	1.122.451	-8.500.667	-1.519.984	-4.284.698
2	9.862.966	1.489.239	5.094.754	-7.494.203	-1.510.761	-3.880.515
3	9.775.033	7.212.169	9.999.592	-6.764.985	-1.778.783	-3.753.578
4	956.761	5.991.663	9.994.963	-5.389.795	-1.400.834	-298.067

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*.

Source: Author's synthesis (Results obtained using Stata17).

5.2. PVAR Lag Order Selection

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 8 lags, are presented in the output table. The MBIC and MQIC are minimized at lag 1, with values of -850.0667 and -428.4698, respectively. The MAIC reaches its minimum value at lag 3 (-177.8783). Hansen's J statistic has high p-values for lags 1 through 7, indicating that the models are not misspecified at these lag lengths and the instruments are valid.

Given the conflicting results from the information criteria, this study follows the recommendation of the majority. Since two of the three criteria (MBIC and MQIC) suggest an optimal lag length of one, a lag order of 1 is selected for the PVAR model estimation. This choice is also the most parsimonious, reducing the number of parameters to be estimated.

5.3. 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.

5.3.1. 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 5, confirm that the model is well-specified.

Table 5. Diagnostic test results.

Test	(1) gGDP	(2) Zscore	(3) NIM	(4) NPL	(5) NII
Arellano-bond autocorrelation test					
AR(1) (p-value)	0.313	0.001	0.060	0.081	0.069
AR(2) (p-value)	0.747	0.687	0.781	0.377	0.314
Hansen test for instruments					
Hansen test (p-value)	1.000	1.000	1.000	1.000	1.000

Source: Author's synthesis (Results obtained using Stata17).

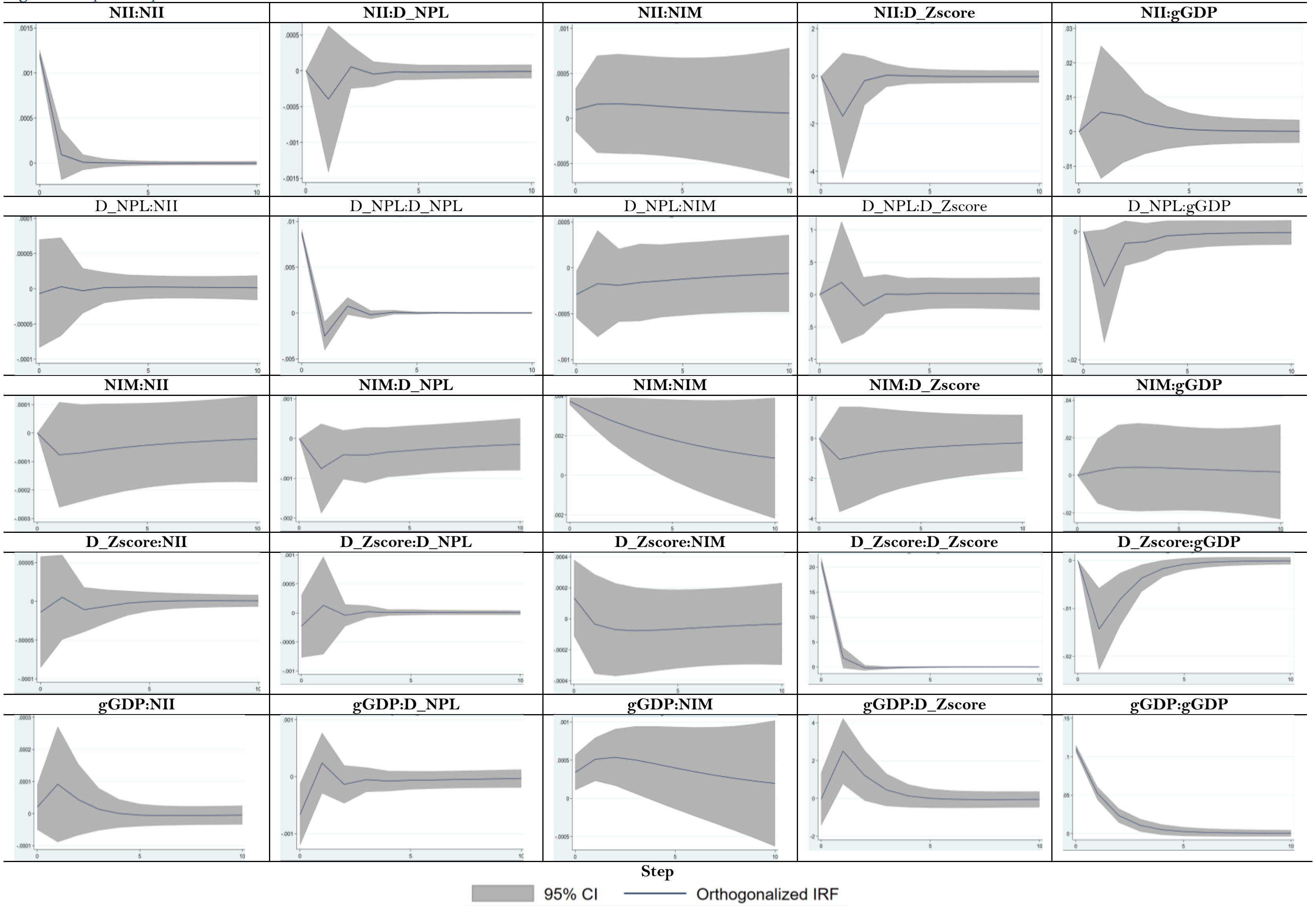
First, the Arellano-Bond test for serial correlation was performed. The critical test for second-order serial correlation (AR(2)) yields high p-values across all five model equations (ranging from 0.314 to 0.781). The failure to reject the null hypothesis of no second-order correlation confirms that 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.

5.3.2. 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.

Figure 3. Impulse Repsonse Functions.



Source: Author's synthesis (Results obtained using Stata17).

Bidirectional Relationship: A strong bidirectional relationship is confirmed between economic growth (gGDP) and the change in bank stability (Zscore). A positive shock to gGDP leads to a statistically significant positive response in Zscore, indicating that economic expansion improves banking stability. Conversely, a positive shock to Zscore elicits a significant and immediate negative response in gGDP.

Impact on Profitability: The Net Interest Margin (NIM) responds negatively to shocks from both the economy and from stability measures. A shock to gGDP generates a slow-developing but significant negative response in NIM, while a shock to Zscore causes a sharp, immediate negative dip followed by a slight positive correction.

Other Significant Responses: Non-Performing Loan ratio (NPL) and Non-Interest Income ratio (NII) both exhibit a statistically significant positive response to an initial shock in gGDP.

6. Conclusions

6.1. Impact from GDP Growth to Banking Stability in Vietnam

Based on the D_Zscore: gGDP graph in the IRF matrix, we analyze in detail the impact of a growth shock (gGDP) on the stability of the banking system (D_Zscore) over time.

At the time of the shock, the impact of gGDP on D_Zscore is insignificant. The reaction curve is close to zero and lies within the confidence interval. This suggests that bank stability does not respond immediately to changes in GDP growth.

Q1 – 2 after the shock: The impact of the gGDP shock begins to appear. The response curve increases positively and exceeds the 95% confidence interval. This shows that economic growth has a positive and statistically significant impact on bank stability within 1 to 2 quarters after the shock occurs. A strong economic growth reduces credit risk and increases profitability, thereby improving the Z-score.

Q3 – 5 post-shock: The positive effect persists and peaks around Q3 or Q4. The reaction curve remains above zero and outside the confidence interval, indicating that the positive relationship remains significant. This suggests that it takes some time for the effects of GDP growth on bank profitability, asset quality, and equity to be fully reflected in the Z-score.

Q6–10 after the shock: The impact begins to fade and the response curve tends towards zero. The confidence interval becomes wider and includes the zero line. This implies that, although the initial impact is significant, in the long run, fluctuations in gGDP no longer have as strong an impact on the Z-score as in the short and medium term. Factors internal to the banking system or regulatory policies may become more important in maintaining long-term stability.

Thus, GDP growth will have a positive impact on bank stability in the short term, peaking after 1 year and gradually declining after 1.5 years. This study provides evidence that GDP growth in Vietnam has a positive impact on bank performance, as shown by the composite index Zscore.

Regarding the transmission channel: We seek answers to the mechanism of impact on bank stability through the response shocks to NIM, NII and NPL from GDP. Although we do not find any direct impact from GDP growth on NIM, we find a hint through another relationship: A positive shock from Z-score (stability) has a negative and statistically significant impact on NIM (business efficiency). This may indicate that when banks become more cautious to ensure stability (high Z-score), they have to make a trade-off by accepting lower profit margins to attract customers or comply with regulations.

For the impact on non-interest income (NII), a shock from growth (gGDP) has no significant impact on NII. For the Z-score, a shock from Z-score (bank stability) has a small and statistically insignificant negative impact on NII_P in the short run, as the 95% confidence interval includes zero. This suggests that bank stability does not have a significant impact on its business performance.

The analysis of non-performing loans (NPL) also has similar results to NII, when economic growth has almost no impact on this variable. This seems to be inconsistent with reality, because as analyzed above, strong GDP growth often causes NPL to decrease initially due to high credit growth, then increase sharply after a forced tightening process. However, as presented in the descriptive statistics section, NPL recorded at Vietnamese banks is often very low and almost never reaches the dangerous warning threshold. We believe that the NPL ratio in Vietnam is often mitigated by supportive regulations from the Central Bank, or by accounting standards affecting debt valuation, and finally by debt classification regulations that facilitate banks to improve their balance sheets.

6.2. Transmission Channels Impact and Potential Risks

It can be seen that in the context of NIM decline, which has no specific impact on NII and NPL, Z-score has a positive response to GDP growth, the transmission channel from GDP growth to banking stability in Vietnam is mainly through monetary policy. More specifically, if GDP does not push NIM/NII up and does not pull NPL down significantly, but Z-score still increases, then there is a high probability that GDP is (1) helping to increase Equity/Assets (thanks to retained profits, increased capital, RWA optimization, sale of risky assets, etc.) or (2) reducing σ(ROA) (more stable profits due to less shocks in the macro environment), or (3) increasing ROA not due to net profit (for example, net profit outside of interest, recovery of written-off debt, provision reversal, service income, safe trading, irregular income, etc.).

When ignoring net interest margin (NIM) and ignoring non-performing loan (NPL) improvement, Z-score may look good but lack quality. Indeed, Vietnamese banks are increasing capital buffers and stabilizing profits, instead of focusing on improving NIM and better managing NPL. In other words, Vietnamese banks are still focusing on old loans, but not developing new credit products, and not trying to penetrate new markets to diversify revenue sources and minimize risks. Furthermore, banks are not willing to accept risks, the fact that NPL remains unchanged shows that bank credit is not expanding to new areas, but is still focused on traditional areas, where NPL is restructured, transferred, and skillfully handled by provisions to always be at an ideal level.

6.3. Implications

This study used the PVAR model to assess the dynamic relationship between GDP growth and banking system stability in Vietnam, using Z-score as the main measure. The results of the impulse response function (IRF) and variance decomposition (FEVD) analysis showed some important conclusions:

- Bidirectional relationship: There is a significant bidirectional Granger causality relationship between GDP growth and banking stability1.
- Impact of GDP on banking stability: A positive shock from GDP growth has a positive and statistically significant impact on Z-score in the short run2. This impact peaks after about 1-2 quarters and gradually weakens over time3333. This suggests that sustained economic growth plays an important role in improving banking system stability4.
- Transmission Channel: Although the literature indicates that GDP growth does not have a significant direct impact on NIM, NII or NPL, this study infers that the main transmission channel from GDP growth to banking stability in Vietnam is mainly through monetary policy6. This impact could be due to an increase in equity/assets, a decrease in profit volatility, or an increase in non-core profits7.

The above findings provide some important policy implications for financial regulators and policy makers in Vietnam:

Prioritize banking system stability: It is necessary to maintain and enhance the stability of the banking system as a prerequisite for sustainable economic growth. Although GDP growth may benefit banks, the impact is only in short-term.

Assessing the quality of Z-score: Caution should be exercised when assessing the Z-score. If the Z-score increases without accompanying improvements in NIM and NPL, this may indicate poor quality stability, relying mainly on increasing capital buffers or stabilizing profits rather than improving core business.

Encourage diversification: Policy should encourage banks to develop new credit products and penetrate new markets to diversify income sources and reduce risks. The lack of change in NPL indicates that banks are still focused on traditional areas, lacking risk tolerance and exploring new growth opportunities.

Transparency in reporting: There is a need to increase transparency in reporting NPLs, as the results show that NPLs do not react significantly to other variables, which may not reflect reality due to current accounting regulations and standards.

References

Andrews, D. W. K., & Lu, B. (2001). Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. *Journal of Econometrics, 101*(1), 123-164. https://doi.org/10.1016/S0304-4076(00)00077-4

Beck, R., Jakubík, P., & Piloiu, A. (2013). *Non-performing loans: What matters in addition to the economic cycle?* ECB Working Paper Series No. 1515. European Central Bank.

Borio, C. E. V. (2003). *Towards a macroprudential framework for financial supervision and regulation?* BIS Working Paper No. 128. Bank for International Settlements.

Borio, C. E. V., & Lowe, P. (2002). *Asset prices, financial and monetary stability: Exploring the nexus.* BIS Working Paper No. 114. Bank for International Settlements.

Čihák, M., & Hesse, H. (2010). Islamic banks and financial stability: An empirical analysis. *Journal of Financial Services Research, 38*(2), 95-113. https://doi.org/10.1007/s10693-010-0089-0

Claessens, S., Kose, M. A., & Terrones, M. E. (2011). *Financial cycles: What? How? When?* IMF Working Paper WP/11/76. International Monetary Fund.

Crockett, A. D. (1997). *Why is financial stability a goal of public policy? In Maintaining financial stability in a global economy.* Paper presented at the Jackson Hole Economic Policy Symposium Proceedings. Federal Reserve Bank of Kansas City.

Demirgüç-Kunt, A., & Huizinga, H. (1999). Determinants of commercial bank interest margins and profitability: Some international evidence. *The World Bank Economic Review, 13*(2), 379-408. https://doi.org/10.1093/wber/13.2.379

European Central Bank. (2005). *Financial stability review (June).* Frankfurt am Main, Germany: European Central Bank.

Gabrielsson, J. (2023). Competition and stability in the European Union banking sector. *International Advances in Economic Research, 29*(1), 45–62.

International Monetary Fund. (2002). *Financial soundness indicators: Compilation guide.* Washington, DC: IMF.

International Monetary Fund (IMF). (2011). *Global financial stability report: Durable financial stability – getting there from here.* Washington, DC: IMF.

Kohlscheen, E., Murcia Pabón, A., & Contreras, J. (2018). *Determinants of bank profitability in emerging markets.* BIS Working Paper No. 686. Bank for International Settlements.

Pesaran, M. H. (2004). *General diagnostic tests for cross section dependence in panels.* CESifo Working Paper Series, No. 1229, Center for Economic Studies and Ifo Institute (CESifo), Munich.

Reinhart, C. M., & Rogoff, K. S. (2009). *This time is different: Eight centuries of financial folly.* Princeton, NJ: Princeton University Press.

Schularick, M., & Taylor, A. M. (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. *American Economic Review, 102*(2), 1029–1061. https://doi.org/10.1257/aer.102.2.1029

Wanke, P., Adhikari, D., & Shah, A. (2016). Predicting bank distress in emerging markets: Evidence from the CAMELS framework. *Journal of Banking & Finance, 73*, 77-89.

World Bank. (2005). *Bank Z-score (GFDD.SI.01) — metadata. Global financial development database.* Washington, DC: World Bank.