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Income Diversification, Credit Risk, Liquidity Concentration, and Bank Stability: Testing Competing Risk Transmission Mechanisms in Indonesian Banking

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ABSTRACT

Purpose – This study examines the effects of income diversification, credit risk, and liquidity concentration on bank stability and assesses whether their joint effects reflect compounding or buffering mechanisms in Indonesian conventional banks during 2019–2025.
Design/methodology/approach – The study uses a balanced panel of 38 conventional commercial banks listed on the Indonesia Stock Exchange from 2019 to 2025. The analysis employs Two-Step System GMM, with alternative panel estimators used for robustness checks.
Findings/Results – Credit risk has a negative and significant effect on bank stability ($\beta = -10.03$; $p < 0.01$), while income diversification and liquidity concentration show no significant direct effects. The interaction between credit risk and liquidity concentration is positive and significant ($\beta = 33.79$; $p < 0.01$), whereas the income diversification–credit risk interaction is marginally significant. The three-way interaction is not significant ($\beta = -55.64$; $p = 0.696$), providing no support for either the compounding or buffering mechanism at the simultaneous three-way level.
Originality/Value – This study advances banking-risk research by testing competing interaction mechanisms rather than assuming purely independent or fully interactive risk effects. The findings indicate that risk transmission in Indonesian banks is characterized more by pairwise interactions than by a simultaneous three-way mechanism.

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1. Introduction

Banks perform the financial intermediation function by transforming liquid liabilities into illiquid credit assets, thereby inherently giving rise to credit risk and liquidity concentration simultaneously (Berger and Bouwman 2009; Wagner 2007). Failure to manage these two risks has direct implications for bank stability (Ghenimi et al. 2017; Imbierowicz and Rauch 2014).
The COVID-19 pandemic exacerbated this risk exposure through two channels: (1) an increase in non-performing loans due to weakened debtor repayment capacity, and (2) liquidity pressure from large-scale withdrawals. In response, banks in Indonesia adopted income diversification strategies by shifting the composition of interest income toward fee-based and trading income. Theoretically, based on *Modern Portfolio Theory*, diversification is an effective mechanism for reducing risk by distributing exposure across various income sources that do not move in the same direction (Markowitz 1952; Asif and Akhter 2019).
Several studies confirm that income diversification makes a positive contribution to bank stability (Ghenimi et al. 2017; Wang and Lin 2021), while Lee et al. (2020) and Tran et al. (2020) find a negative impact due to increased operational complexity and agency problems, and some even find no significant relationship (Abuzayed et al. 2018). Moudud-Ul-Huq (2019) and Wang and Lin (2021) explain this inconsistency through bank-specific characteristics and institutional governance conditions.
Credit risk and liquidity concentration have a mutually reinforcing relationship: debtor defaults affect liquidity, while liquidity pressure drives asset liquidation below its economic value, which ultimately worsens credit quality (Diamond and Rajan 2000; Wagner 2007). This *compounding risk* logic indicates that the interaction of the three risk dimensions should weaken, rather than strengthen, bank stability. On the other hand, income diversification can theoretically function as a *buffer* when interest income is under pressure, so the interaction among the three may also potentially produce a neutralizing effect. Duong et al. (2025), in a study of an ASEAN-5 bank sample, indicate that although income diversification can partially increase short-term liquidity concentration exposure, in an advanced model specification diversification instead reduces liquidity concentration and functions as a *buffer* against financial shocks, supporting an initial indication of a *buffering* mechanism at the regional ASEAN level. In addition to these two interactive mechanisms, there is a third possibility that has received relatively limited exploration: these three risk dimensions may also transmit their effects on bank stability independently (*independent risk transmission*), meaning that credit risk, liquidity concentration, and income diversification affect bank stability through separate channels and neither reinforce nor neutralize one another. This mechanism is theoretically consistent with banking risk governance structures in many developing countries, where regulations on credit risk management, liquidity adequacy, and non-interest income strategies are supervised through different *prudential* frameworks (Financial Services Authority), and organizationally are often managed by work units that are not always integrated. The three potential mechanisms—*compounding*, *buffering*, and independent transmission—have not been directly tested in the context of Indonesian conventional banking, so the nature of this combined risk transmission remains an open empirical question that is the main focus of this study.
In the context of banking stability, the interaction among income diversification, credit risk, and liquidity concentration is expected to operate through three *competing mechanisms*. First, the *compounding* mechanism, in which deteriorating credit risk and liquidity pressure reduce the benefits of diversification and thereby lower bank stability (Diamond & Rajan, 2000;

Wagner, 2007). Second, the *buffering* mechanism, in which non-interest income is able to dampen the impact of credit and liquidity risk and thereby strengthen stability (Wang & Lin, 2021). Third, the *independent risk transmission* mechanism, in which each risk is managed separately and therefore affects stability additively without significant interaction. Because these three mechanisms are supported by different theoretical foundations, this study tests the relationships through a competing-hypotheses framework.

This study aims to test whether income diversification, credit risk, and liquidity concentration transmit their effects on the stability of conventional commercial banks listed on the Indonesia Stock Exchange independently (additively) or interactively (*compounding/buffering*) during the 2019-2025 period. This observation period was selected to cover three relevant phases of banking macroeconomic dynamics, namely the pre-pandemic period, pandemic pressure, and post-pandemic recovery, as an empirical context for testing the proposition of *independent risk transmission* in the Indonesian institutional setting, while also evaluating whether the indication of an income-diversification buffering mechanism against risk found at the ASEAN-5 regional level (Duong et al. 2025) applies consistently in a single-country emerging-market context measured through bank stability (Z-score), or is instead constrained by specific domestic institutional conditions. Estimation is conducted using the *Two-Step System Generalized Method of Moments* (System GMM) developed by Arellano and Bover (1995) and Blundell and Bond (1998). This method was selected because it can address endogeneity problems, unobserved individual heterogeneity, and panel dynamics through the use of internal instruments based on variable lags. The findings of this study are expected to provide a theoretical contribution by confirming the proposition of *independent risk transmission* as an alternative framework to the risk-interaction approach that dominates the literature, while also offering an institutional explanation of conditions under which risk transmission is additive rather than synergistic in a single emerging-market banking system. Practically, these findings imply that regulators and bank management need to address each dimension of credit risk, liquidity, and income diversification separately and systematically, rather than relying on synergistic effects across risk dimensions.

2. Literature Review & Hypothesis Development

2.1 Bank Stability from the Financial Intermediation Perspective

Bank stability needs to be explained from the intermediation function: banks collect short-term funds and channel them into long-term credit. This pattern creates maturity, credit, and liquidity risks. Djebali and Zaghdoudi (2020) emphasize that credit and liquidity risks can reduce bank stability at certain levels. Demirgüç-Kunt et al. (2021) show that the pandemic put pressure on global banking performance, although liquidity policies helped mitigate its impact. The *Z-score* is relevant because it combines profitability, capital, and earnings volatility in a single measure of stability.

2.2 Income Diversification and Bank Stability

Income diversification is undertaken by banks to reduce dependence on interest income through fee-based income, commissions, *treasury*, and other non-interest activities. In theory, diversification can reduce risk if income sources do not move in the same direction. However, its impact is not always positive. Abbas and Ali (2022) find that diversification can reduce bank risk, but Adesina (2021) emphasizes that its benefits depend on human capital. Tariq et al. (2014) also show that stability is influenced by bank maturity, while Mehmood and De Luca (2023) find that non-interest income can increase credit risk.

2.3 Credit Risk and Bank Stability

Credit risk arises when debtors fail to meet their obligations to the bank. An increase in credit risk depresses profits, increases allowance for impairment losses (CKPN), reduces capital, and weakens bank stability; its impact also extends to liquidity because non-performing loans reduce cash inflows. Nguyen and Nguyen (2023) emphasize that credit risk has an important effect on bank stability. Djebali and Zaghdoudi (2020) also show that credit and liquidity risks can put pressure on stability at certain levels.

2.4 Liquidity Concentration and Bank Stability

Liquidity concentration arises when a bank is unable to meet short-term obligations without incurring substantial losses; this risk stems from depositor withdrawals and difficulty selling assets at fair value. Djebali and Zaghdoudi (2020) show that liquidity concentration and credit risk can reduce bank stability at certain levels. Duong et al. (2025) also find that income diversification is related to liquidity concentration in ASEAN-5 banks. Therefore, LIQHHI is relevant for examining the concentration of liquid, semi-liquid, and illiquid assets.

2.5 Interaction of Income Diversification, Credit Risk, and Liquidity Concentration

Bank stability is influenced by the joint relationship among income diversification, credit risk, and liquidity concentration. Diversification can act as a buffer when interest income declines, but its benefits weaken when credit and liquidity risks increase. Nguyen and Nguyen (2023) emphasize that income diversification and credit risk affect bank stability. Djebali and Zaghdoudi (2020) also show that credit and liquidity risks can put pressure on stability at certain levels. Therefore, the interaction among IDIV, CRISK, and LIQHHI is important to test empirically.

2.6 Hypothesis Development

H1: Income diversification has a negative effect on the stability of conventional commercial banks in Indonesia.

Based on Modern Portfolio Theory, income diversification can strengthen bank stability and has a direct effect (Alouane and Haddou, 2026), because banks do not depend solely on interest income. Non-interest activities can increase operational complexity, information asymmetry, and managerial risk as explained through the Agency Theory perspective, but the effect of income diversification can also be negative if it is not yet supported by a strong risk-management system.

H2: Credit risk has a negative effect on the stability of conventional commercial banks in Indonesia.

Nguyen and Nguyen (2023) state that high credit risk can reduce the quality of bank assets as measured by the *Z-score*, increase reserve expenses, depress profits, and reduce bank capital capacity, which can shorten the distance to insolvency risk, because an increase in credit risk is predicted to reduce bank stability.

H3: Liquidity concentration has a negative effect on the stability of conventional commercial banks in Indonesia.

Liquidity concentration reflects an imbalance in the structure of bank assets and liabilities and can exert pressure in certain situations (Djebali and Zaghdoudi 2020), because of excessive concentration in illiquid assets related to the funding approach. Banks that are too large will certainly also hold liquid assets and may experience a loss of potential income.

H4: The three-way interaction among income diversification, credit risk, and liquidity concentration has a significant effect on the stability of conventional commercial banks in

Indonesia, with the direction of the effect depending on the more dominant mechanism (*compounding* or *buffering*).

- H4: The three-way interaction among income diversification, credit risk, and liquidity concentration has a significant effect on the stability of conventional commercial banks in Indonesia, with the direction of the effect depending on the more dominant mechanism (compounding or buffering).
  H4a (Compounding Mechanism): The simultaneous interaction among income diversification, credit risk, and liquidity concentration has a negative effect on bank stability.
  This hypothesis assumes that high credit risk and liquidity concentration reinforce each other, thereby reducing the benefits of income diversification. Under these conditions, diversification instead increases operational complexity and agency costs, so the interaction among the three reduces bank stability.
- H4b (Buffering Mechanism): The simultaneous interaction among income diversification, credit risk, and liquidity concentration has a positive effect on bank stability.
  This hypothesis is based on Modern Portfolio Theory, which views income diversification as a buffering mechanism. When banks face increasing credit risk and high liquidity concentration, non-interest income (fee-based income) can reduce cash-flow pressure so that the interaction among the three variables supports bank stability.
  H4a and H4b are formulated as competing hypotheses because they predict opposite directions of effect for the same three-way interaction. H4a predicts a negative coefficient (compounding), while H4b predicts a positive coefficient (buffering). Because both are tested from the same three-way interaction coefficient, only one can be supported, or neither can be supported if the coefficient is not significant.

3. Methodology

3.1 Sample and Data

The study population consists of conventional commercial banks listed on the Indonesia Stock Exchange (IDX) during the 2019-2025 period. Conventional banks were selected because they have operational characteristics, income structures, and risk profiles that differ from Islamic banks, so the research results are more consistent in analyzing banking stability. The sample was selected using a *purposive sampling* technique with specific criteria to ensure the availability of complete data for all research variables. Based on these criteria, the final sample consisted of conventional commercial banks that met all observation requirements as detailed in Table 1.

Table 1. Sample Selection

No	Sample Selection Stage 2019-2025	Number of Banks
1	Commercial banks continuously listed on the IDX during the 2019-2025 period	48
2	Islamic Banks	-4
3	Subsidiaries	
	Population of Conventional Commercial Banks	**44**

4	Banks that do not meet the data-completeness criteria for the variables, or experienced corporate actions or changes (mergers, acquisitions, and delistings) during 2019-2025.	-6
	Final Sample Size	**38**
	Total Observations: 38 banks x 7 years	**266**

The 2019-2025 period was selected because it reflects the acceleration phase of digital transformation in the Indonesian banking industry. The basis and justification for selecting the observation period are presented in Table 2.

Table 2. Justification of the Observation Period and Phases of Banking Digital Transformation

Year	**Assumption**	**Source**
2019	Initial increase in the adoption of digital banking services,	BI, 2019
2020	COVID-19 pandemic shock period,	BI, 2020
2021	Acceleration of national digital payment-system integration,	OJK, 2021
2022	Economic recovery, increased intensity of digital banking services,	Stefanelli et al. (2022)
2023	Strengthening of the digital banking business model,	BI, 2023
2024	Increased efficiency and stabilization of the bank digital business model, financial resilience, and banking-industry competitiveness,	OJK, 2024
2025	Maturity of banking digital transformation.	OJK, 2025

3.2 Types and Sources of Research Data

This study uses an explanatory quantitative approach based on secondary panel data. Bank financial data were obtained from annual reports and financial statements published through the official IDX *website* and the *website*s of each bank.

3.3 Operational Definitions of Variables

3.3.1 Dependent Variable

Bank stability is measured using the Z-score, an indicator that shows a bank's distance from insolvency (distance to default) and has been widely used in the banking-stability literature (Laeven & Levine, 2009). The higher the Z-score, the more stable the bank. The Z-score is calculated as follows:

$$Z_{i,t} = \frac{ROA_{i,t} + \left(\frac{Equity}{TotalAssets}\right)_{i,t}}{\sigma(ROA)_i}$$

where $ROA_{i,t}$ is *return on assets* of bank *i* in period *t*, $(Equity/Total\ Assets)_{i,t}$ is the capital ratio, and $\sigma\ (ROA)_i$ is the standard deviation of ROA calculated for each bank over the entire observation period, following Beck, De Jonghe, and Schepens (2013).

Because the Z-score distribution is generally *right-skewed*, this study uses a natural logarithmic transformation of the Z-score to reduce distributional skewness and improve the quality of model estimation, as carried out in previous studies (Čihák & Hesse, 2010; Beck, De Jonghe, & Schepens, 2013).

$$BSTAB_{i,t} = ln\ ln\ (Z_{i,t})$$

The occurrence of negative $BSTAB$ values in the descriptive statistics occurs mathematically when the raw Z-score lies in the range $0 < Z_{it} < 1$ (because $\ln(x) < 0$ for every $x \in (0,1)$). This does not indicate negative capital ratios or returns. All raw Z-score observations in the sample are strictly positive ($Z_{it} > 0$), so no constant addition or data *truncation* is required before the logarithmic transformation is performed. The interpretation of the regression coefficients (including *Credit Risk*) is adjusted to the log-linear transformation scale.

3.3.2 Independent Variables

Income Diversification (IDIV) – calculated using a modified *Herfindahl-Hirschman Index* (HHI) of income (Wang & Lin, 2021).

$$IDIV_{i,t} = 1 - \left[\left(\frac{InterestIncome}{TotalIncome}\right)^2 + \left(\frac{Non - InterestIncome}{TotalIncome}\right)^2\right]$$

Credit Risk (CRISK) - proxied by the ratio of CKPN expense to gross loans (Abbas & Ali, 2021)

$$CRISK_{i,t} = \frac{LoanLossProvision}{GrossLoan}$$

Liquidity Concentration (LIQHHI) – measured through an HHI-based asset concentration index that distinguishes between liquid and illiquid assets (Berger and Bouwman, 2009).

$$LIQHHI_{i,t} = 1 - \left[\left(\frac{LiquidAssets}{TotalAssets}\right)^2_{i,t} + \left(\frac{Semi - LiquidAssets}{TotalAssets}\right)^2_{i,t} + \left(\frac{IlliquidAssets}{TotalAssets}\right)^2_{i,t}\right]$$

3.4 Model and Data Analysis Techniques

The research model is estimated using dynamic panel data regression with the *Two-Step System Generalized Method of Moments* (System GMM) approach developed by Arellano and Bover (1995) and Blundell and Bond (1998). This method was selected for the *robustness check* because of its ability to address potential endogeneity from reciprocal relationships among risk variables, individual heterogeneity (*unobserved fixed effects*), dynamic problems involving *lag*ged dependent variables, and autocorrelation that commonly occurs in dynamic banking panel data.

Before the main regression, the study conducts feasibility testing. Identification of the initial model specification is tested through the Chow Test, Hausman Test, and Lagrange Multiplier (LM) Test. Validation of the System GMM model is specifically tested by meeting the requirement that the number of instruments must be smaller than the number of *cross-section*s, the Hansen test (*p-value* > 0.05), and the Arellano-Bond AR(2) test (*p-value* > 0.05).

To address the problem of extreme multicollinearity in the interaction model, in which the *Variance Inflation Factor* (VIF) can mechanically inflate, this study applies a *mean-centering* procedure before estimation. All continuous independent variables (IDIV, CRISK, and LIQHHI) are centered by subtracting the sample mean from each observed value. This procedure stabilizes the model, normalizes VIF values, and prevents inflated standard errors without changing the interpretive meaning of the marginal coefficients.

The regression analysis is developed hierarchically through three specifications to test all hypotheses in one comprehensive equation, with the mathematical model as follows:

$$\begin{aligned} BSTAB_{i,t} = \alpha &+ \beta_1 BSTAB_{i,t-1} + \beta_2 IDIV_{i,t} + \beta_3 CRISK_{i,t} + \beta_4 LIQHHI_{i,t} \\ &+ \beta_5 (IDIV \times CRISK)_{i,t} + \beta_6 (CRISK \times LIQHHI)_{i,t} + \beta_7 (IDIV \times LIQHHI)_{i,t} \\ &+ \beta_8 (IDIV \times CRISK \times LIQHHI)_{i,t} + \varepsilon_{i,t} \end{aligned}$$

Description:
i = Bank entity
t = Observation year
BSTAB = Bank stability
IDIV = Income diversification
CRISK = Credit risk
LIQHHI = Liquidity concentration
α = Constant
β = Regression coefficient
ε = *Error term*

The criteria for hypothesis acceptance are set at a significance level of *p-value* < 0.05. The first through third hypotheses are analyzed based on direct effects as well as *two-way interaction*s, while the fourth hypothesis is evaluated through the significance of the *three-way interaction* coefficient. Because the fourth hypothesis is formulated as competing hypotheses, significance with a negative coefficient will support H4a (*compounding*), significance with a positive coefficient will support H4b (*buffering*), while empirical non-significance will lead to the alternative mechanism, namely independent risk transmission (*independent transmission*).

3.5 Variable Measurement

The lagged dependent variable ($BSTAB_{i,t-1}$) introduces dynamic endogeneity that causes bias in both *Fixed-Effects* and *Random-Effects* estimators. The *Two-Step System GMM* estimator (Arellano & Bover, 1995; Blundell & Bond, 1998) addresses this by using lagged *level* variables as instruments for the *first-difference* equation, and lagged *difference* variables as instruments for the *level* equation.

In the econometric software model specification (xtabond2), only the lagged dependent variable (L.BSTAB) is treated as an endogenous variable. The GMM instruments for L.BSTAB use the second and third lags with the collapse option to prevent instrument proliferation. Meanwhile, IDIV, CRISK, LIQHHI, and all interaction terms are treated as standard instruments (IV-style) in the *level* equation, because these variables are considered predetermined with respect to current-period bank stability.

The accuracy of the model specification is evaluated through two main tests: the Hansen J Test to ensure the overall validity of the instruments (overidentifying restrictions), and the Arellano-Bond AR(2) Test to ensure the absence of second-order serial autocorrelation in the first-difference residuals. As a reliability test, the System GMM results are also compared with the Fixed Effects and Difference GMM estimators (Arellano & Bond, 1991) to verify that the dynamic System GMM specification is the most appropriate approach.

The *marginal effects* of income diversification on bank stability under various risk scenarios are calculated based on the full partial derivative of the Model 3 equation:

$$\frac{\partial BSTAB_{i,t}}{\partial \tilde{IDIV}_{i,t}} = \beta_1 + \beta_4 \tilde{CRISK}_{i,t} + \beta_5 \tilde{LIQHHI}_{i,t} + \beta_7\left(\tilde{CRISK}_{i,t} \times \tilde{LIQHHI}_{i,t}\right)$$

The formula above ensures that the marginal-effects analysis accommodates all interaction effects simultaneously, thereby avoiding static or *flat* estimates at different risk levels.

4. Result and Discussion

4.1 Descriptive Statistics

All observation units were confirmed to have no missing values in Stata. The mean, standard deviation, minimum value, and maximum value are presented in Table 3.

Table 3. *Descriptive Statistics of Main Variables*

Variable	Obs.	Mean	Std. Dev.	Min.	P25	Median	P75	Max.	Skew.	Kurt.
BSTAB	266	3.1887	1.1037	-3.6452	2.8036	3.3151	3.9404	4.9773	-1.7244	8.9412
IDIV	266	0.2142	0.1092	0.0000	0.1401	0.2062	0.2932	0.5000	0.2817	2.5200
CRISK	266	0.0261	0.0394	0.0000	0.0070	0.0151	0.0307	0.3305	4.4621	27.8043
LIQHHI	266	0.3463	0.1379	0.0201	0.2472	0.3288	0.4356	0.8401	0.7740	4.0067

Source: Stata processing output, bank panel data 2019-2025.

The descriptive-statistics results show relatively high variation across banks, especially in the credit-risk and bank-stability variables, indicating heterogeneity in financial conditions and risk structures in the Indonesian banking industry during the study period.

Based on the test results, the bank-stability variable (BSTAB) shows that the stability level of Indonesian conventional banks is relatively good, although there is still variation across banks during the study period; some banks experience fairly high stability pressure, some banks have very strong stability conditions, most banks have relatively high stability levels, the distribution is leptokurtic, and there are indications of extreme observations in the bank-stability variable.

The income-diversification variable (IDIV) shows that the level of income diversification among Indonesian conventional banks remains relatively low; some banks still depend entirely on interest income, no bank has yet reached a very high level of income diversification, the distribution is close to normal, and the transition toward non-interest income sources is still taking place gradually in the Indonesian banking industry.

The credit-risk variable (CRISK) indicates variation in credit risk across banks during the study period, including banks with very good credit quality and banks with very high credit risk; most banks have low credit risk, but several banks have extreme credit risk, and there are outliers in the credit-risk variable.

The liquidity-concentration variable (LIQHHI) shows variation in liquidity concentration across Indonesian conventional banks; some banks have very low liquidity concentration, some have very high liquidity concentration, most banks have low to moderate levels of liquidity concentration, and there are several extreme observations in the liquidity-concentration variable.

4.2 Correlation Test

Bivariate correlation analysis using the Pearson method to detect potential multicollinearity in the relationship between the dependent and independent variables is presented in Table 4.

Table 4. Correlations among Main Variables

Variable	BSTAB	IDIV	CRISK	LIQHHI
BSTAB	1.0000			
IDIV	-0.1124 (0.067)	1.0000		
CRISK	-0.4426*** (0.000)	0.0567 (0.357)	1.0000	
LIQHHI	-0.0239 (0.698)	0.2031*** (0.001)	0.0630 (0.306)	1.0000

Source: Stata processing output, bank panel data 2019-2025.

*Note: p-value; *** p<0.01; ** p<0.05; * p<0.10*

The correlation analysis results show that credit risk (CRISK) has a significant negative correlation with bank stability (BSTAB); the correlation coefficient indicates that an increase in credit risk consistently reduces bank stability. Income diversification (IDIV) shows a negative correlation with BSTAB, although it is not statistically significant. The liquidity-concentration variable (LIQHHI) shows a very weak and insignificant correlation with BSTAB, meaning that there is a high correlation among the interaction variables. However, this structural property is inherent in the construction of interaction variables and is not a multicollinearity problem that needs to be addressed in System GMM estimation (Wooldridge 2022).

4.3 Multicollinearity Test (VIF)

The multicollinearity test for calculating the Variance Inflation Factor (VIF) is conducted using a diagnostic OLS regression rather than the final estimation, as shown in Table 5.

Table 5. VIF Test Results

Variable	VIF (C)	Description
IDIV × CRISK × LIQHHI	1.62	Three-way interaction
IDIV_CRISK	1.52	Two-way interaction
CRISK_LIQHHI	1.29	Two-way interaction
IDIV_LIQHHI	1.39	Two-way interaction
CRISK	1.25	Main variable
IDIV	1.22	Main variable
LIQHHI	1.20	Main variable
Mean VIF	1.35	

Source: Stata processing output, bank panel data 2019-2025.

The multicollinearity test for calculating the Variance Inflation Factor (VIF) is conducted using a diagnostic OLS regression rather than the final estimation, as presented in Table 5. The VIF test results after mean-centering show that all main independent variables and interaction variables have VIF values below the conventional threshold of 10, with a maximum value of 1.62 (three-way interaction) and a mean VIF of 1.35. This finding indicates that the mean-centering procedure applied to the continuous variables (IDIV, CRISK, and LIQHHI) has successfully addressed the potential extreme multicollinearity that commonly arises in polynomial interaction models (Brambor et al., 2005; Wooldridge, 2022). Accordingly, the coefficient estimates and standard errors generated by the System GMM model are not affected by a significant multicollinearity problem.

4.4 Stationarity Test (Levin-Lin-Chu)

The stationarity test uses the Levin-Lin-Chu (LLC) test, designed for panel data under the assumption of homogeneous autoregressive parameters (Levin et al. 2022). The LLC test was selected because the panel structure of this study is balanced with N=38 and T=7, which falls into the short-wide panel category and is an optimal domain for the LLC method. The null hypothesis (H0) states that all panels contain a unit root (non-stationary), while the alternative hypothesis (H1) states that all panels are stationary, as shown in Table 6.

Table 6. Levin-Lin-Chu Stationarity Test Results

Variable	Adjusted t*	p-value	Conclusion
BSTAB	−23.1005	0.0000	Stationary (Reject H0)
IDIV	−32.2427	0.0000	Stationary (Reject H0)
CRISK	−31.9551	0.0000	Stationary (Reject H0)
LIQHHI	−49.6965	0.0000	Stationary (Reject H0)

Source: Stata processing output, bank panel data 2019-2025.

The test results reject the null hypothesis for all four variables. Thus, all variables are classified as stationary, allowing level regression estimation without the risk of spurious relationships due to non-stationarity (Hadri 2000).

The stationarity condition supports the validity of using System GMM, because this method assumes variable stationarity to generate valid instruments from lags of endogenous variables. In a banking-panel setting, these results indicate that financial ratios standardized by total assets or total income tend to exhibit mean-reverting properties that produce stationarity at that level (Cipollini and Fiordelisi 2012).

4.5 Hausman Test

The Hausman Test, used to compare the consistency of the Fixed Effect (FE) and Random Effect (RE) estimators, tests the orthogonality between the independent variables and unobserved individual effects. Failure to reject H0 indicates that there is no systematic difference between the FE and RE estimators, meaning that the unobserved individual effects are not correlated with the independent variables (Elisa et al., 2025), as shown in Table 7.

Table 7. Hausman Test Results

Component	Value	Description
Chi-square	9.37	There is a systematic difference in coefficients
p-value	0.0248	*p < 0,05*
Decision	Reject H0	Random Effect is not the primary choice
More consistent panel model	Fixed Effect	Individual bank effects need to be controlled

Source: Stata processing output, bank panel data 2019-2025.

The p-value is < 0.05, so the hypothesis is rejected, and the Fixed Effect estimator is therefore more consistent than the Random Effect estimator. This rejection of H0 methodologically strengthens the justification for using System GMM as the main estimator, because System GMM not only addresses unobserved heterogeneity, which is a weakness of RE, but also simultaneously addresses endogeneity and panel dynamics that cannot be accommodated by the standard FE estimator (Roodman 2009).

The most pronounced coefficient difference between FE and RE is found in the CRISK variable, with the FE and RE coefficients showing a correlation between individual bank effects and the level of credit risk. This condition indicates that bank credit-risk management policies are strongly influenced by specific institutional characteristics that remain constant over time, such as risk culture, management competence, and business strategy (Srairi 2013).

4.6 Two-Step System GMM Estimation Results

The dynamic model is estimated using the Two-Step System GMM method implemented through the xtabond2 command in Stata with the Two-Step Robust Small option to generate standard errors robust to heteroskedasticity and autocorrelation. The instrument specification uses the second and third lags of the lagged dependent variable (L.BSTAB) as GMM instruments with the collapse option to prevent instrument proliferation, while the independent variables are treated as standard instruments in the level equation (Table 8).

Table 8. Two-Step System GMM Model Diagnostics

Diagnostic Indicator	Result	Criterion	Decision
Number of instruments	11	Smaller than the number of groups (38)	Pass

Number of groups	38	Matches the number of banks	Pass
Number of observations	228	Effective data after lag	Pass
Prob > F	0.0000	Less than 0.05	Model is significant
AR(1) p-value	0.705	Additional information	No first-order autocorrelation
AR(2) p-value	0.313	Greater than 0.05	Pass
Sargan p-value	0.510	Greater than 0.05	Instruments are not problematic
Hansen p-value	0.786	Greater than 0.05	Valid instruments
Difference-in-Hansen p-value	0.497	Greater than 0.05	Valid instrument subset

Source: Stata processing output, bank panel data 2019-2025.

Based on the tests, the model meets the three main System GMM requirements. The number of instruments does not exceed the number of groups, the Hansen test indicates valid instruments, and the AR(2) test indicates the absence of second-order autocorrelation. Accordingly, the model coefficients can be interpreted (Table 9).

Table 9. Estimation Results for Main Variables

Variable	Coefficient	Std. Err.	t-stat	p-value	Significance
L.BSTAB	−0.0961	0.5063	−0.19	0.851	Not significant
IDIV	−0.6929	0.6428	−1.08	0.288	Not significant
CRISK	−10.0251	2.4820	−4.04	0.000	Significant at 1%
LIQHHI	−0.3044	0.5003	−0.61	0.547	Not significant
Constant	3.5021	1.6713	2.10	0.043	Significant at 5%

*Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$; ns = not significant*

Source: Stata processing output (2026), bank panel data 2019-2025.

The estimation results show that L.BSTAB has no significant effect ($p = 0.851$), indicating that bank stability in the previous period does not affect stability in the current period. This condition is suspected to be influenced by structural disruptions during the COVID-19 pandemic that altered the persistence pattern of banking stability (Goetz et al., 2016).

The credit-risk variable (CRISK) has a negative and significant effect ($p = 0.000$) and is the most dominant factor in the model. Because BSTAB is the natural logarithm of the Z-score, the coefficient $\beta = -10.025$ is not interpreted directly in Z-score units. An increase in CRISK of 0.01 (1 percentage point) is associated with a decrease in BSTAB of 0.10025, which is equivalent to a decrease in the Z-score of approximately 9.5% based on the equation $\%\Delta Z\text{-score} \approx \beta \times \Delta CRISK \times 100\%$, *ceteris paribus*. This finding indicates that increased credit risk is associated with weakened bank stability, consistent with Bect et al. (2022) and Fiordelisi et al. (2011).

Conversely, income diversification (IDIV) and liquidity concentration (LIQHHI) have no significant effect ($p > 0.10$), so after mean-centering, these two variables have no direct effect on bank stability.

For the interaction variables, IDIV×CRISK and CRISK×LIQHHI have significant effects, whereas IDIV×LIQHHI and IDIV×CRISK×LIQHHI are not significant. These findings show interactions in several pairs of risks, but there is no three-way synergistic effect, so risk transmission to bank stability does not occur simultaneously. The non-significance of this three-way interaction indicates that no full synergy effect across risk dimensions is statistically detected in this sample. However, this finding cannot be interpreted as confirmation that each risk channel operates independently (Table 10).

Table 10. Estimation Results for Interaction Variables

Variable	Coefficient	Std. Err.	t-stat	p-value	Significance
IDIV × CRISK	52.1765	27.3524	1.91	0.064	Significant at 10%
CRISK × LIQHHI	33.7906	6.8862	4.91	0.000	Significant at 1%
IDIV × LIQHHI	1.7750	3.0610	0.58	0.566	Not significant
IDIV × CRISK × LIQHHI	−55.6397	141.1338	−0.39	0.696	Not significant

*Note: *** p < 0.01; ** p < 0.05; * p < 0.10; ns = not significant*

Source: Stata processing output (2026), bank panel data 2019-2025.

The estimation results show that the relationships among the risk variables are not entirely uniform. Of the four interaction components tested, the IDIV × CRISK interaction shows a positive coefficient of 52.1765 with a p-value of 0.064. This result is not significant at the 5% level, but shows marginal significance at the 10% level. The positive coefficient indicates that, when other variables are held constant, an increase in credit risk tends to shift the effect of income diversification on bank stability in a more positive direction or reduce its negative effect. However, because the statistical evidence is only at the 10% level, this finding should be treated as an initial indication rather than strong evidence of a *buffering* mechanism. Further interpretation also needs to consider all interaction components through marginal-effects analysis, rather than only the sign of the individual interaction coefficient.

The CRISK × LIQHHI interaction shows a stronger result, with a positive coefficient of 33.7906 and significance at the 1% level ($p < 0.01$). This finding shows that the relationship between credit risk and bank stability statistically depends on the degree of concentration in the asset structure by liquidity. With the main CRISK coefficient being negative, the positive sign of the interaction indicates that an increase in LIQHHI tends to weaken the magnitude of the negative effect of credit risk on bank stability, holding other variables constant. Nevertheless, this result cannot automatically be interpreted as evidence that liquidity concentration is a risk-mitigation mechanism. LIQHHI measures the degree of concentration in the asset structure and does not directly indicate whether that concentration is in more liquid or less liquid assets. Therefore, the economic interpretation of the CRISK × LIQHHI interaction needs to be made cautiously and confirmed through marginal-effects analysis and alternative liquidity indicators.

Meanwhile, the IDIV × LIQHHI interaction produces a positive coefficient of 1.7750, but it is not statistically significant ($p = 0.566$). This result indicates that the study does not find sufficient statistical evidence that concentration in the asset structure by liquidity moderates the relationship between income diversification and bank stability. This non-significance does not mean that income diversification and liquidity management definitively operate independently; it only shows that the additional interaction effect between them is not detected in the sample and model specification used.

The three-way interaction IDIV × CRISK × LIQHHI also does not show a significant effect on bank stability, with a coefficient of −55.6397 and $p = 0.696$. Thus, neither the *compounding* mechanism, which expects a negative and significant coefficient, nor the *buffering* mechanism, which expects a positive and significant coefficient, receives empirical support at the simultaneous three-way interaction level. This result indicates that the study does not find statistical evidence of an additional effect arising when income diversification, credit risk, and liquidity concentration change simultaneously.

The non-significance of the three-way interaction cannot be used as conclusive evidence that the three dimensions operate independently. In accordance with the nature of interaction models, a non-significant result may be related to limitations in *statistical power*, data variation, variable measurement, or model specification. Therefore, the research finding is more appropriately stated as the absence of a statistically detected simultaneous three-way interaction in the study sample, rather than confirmation of an *independent risk transmission* mechanism.

Overall, Table 10 shows that the structure of risk transmission is more complex than a fully additive or fully interactive framework. There is strong evidence of interaction between credit risk and liquidity concentration, as well as weaker evidence of interaction between income diversification and credit risk. In contrast, the interaction between income diversification and liquidity concentration and the simultaneous three-way interaction do not show statistical significance. These findings indicate that relationships among risk dimensions need to be analyzed conditionally through marginal effects and cannot be concluded solely on the basis of the significance of each interaction coefficient.

4.7 Model Feasibility Test (Wald, Hansen, AR(2))

The validity of the System GMM estimation is determined by three main diagnostic criteria that must be met before the coefficients are interpreted (Table 11).

Table 11. System GMM Model Feasibility Test Results

Diagnostic Test	Statistic	p-value	Conclusion
Wald F (8,37)	F = 215.45	0.000	Pass
Hansen J (chi2)	chi2(2) = 0.48	0.786	Pass
AR(1)	z = 0.38	0.705	Diagnostic note.
AR(2)	z = -1.01	0.313	Pass
Number of Instruments	11	< 38	Pass

Source: Stata processing output, bank panel data 2019-2025.

The Arellano-Bond test for second-order autocorrelation [AR(2)] produces z = -1.01 with a p-value of 0.313, confirming the absence of autocorrelation in the *first-difference residuals*. First-order autocorrelation [AR(1)] in *first-difference residuals* is mechanically generally expected to be significant as a mathematical consequence of the differencing process itself, so it is not an equivalent passing criterion to AR(2). It should be noted that the non-significant AR(1) value (p = 0.705) is an unusual diagnostic anomaly in the *first-difference residuals* of a dynamic panel model. This non-significance of AR(1) is consistent with the weak persistence of bank stability indicated by the non-significant L.BSTAB coefficient (β = -0.0961; p = 0.851), but still requires caution in interpretation. The number of instruments is 11, far smaller than the number of observational units (N=38), thereby avoiding the problem of instrument proliferation (Roodman, 2009). With the Hansen J and AR(2) criteria satisfied, the System GMM model-feasibility requirements are met, and the coefficients can be validly interpreted.

4.8 Marginal Effect and Margin Plot

The marginal-effects analysis evaluates whether the effect of income diversification (IDIV) on bank stability (BSTAB) changes significantly under different conditions of credit risk (CRISK) and liquidity concentration (LIQHHI).

In a model containing interaction variables, the signs of some independent-variable coefficients are not sufficient to interpret conditional effects; therefore, marginal effects calculated at various moderator values provide a more informative approach (Brambor et al. 2005; Berry et al. 2012) (Table 12).

Table 12. Summary of the Marginal Effect of IDIV on BSTAB

Moderation Condition	Setter Value	dy/dx (IDIV)	Std. Err.	p-value	Decision
Low CRISK	0.01	-1.53	0.684	0,025**	Significant Negative
Moderate CRISK	0.03	-0.486	0.677	0.472	Not Significant
High CRISK	0.05	0.556	1.023	0.586	Not Significant
Low LIQHHI	0.2	-0.952	0.725	0.189	Not Significant
Moderate LIQHHI	0.33	-0.721	0.637	0.257	Not Significant
High LIQHHI	0.45	-0.508	0.758	0.502	Not Significant

Source: Stata processing output, bank panel data 2019-2025.

The marginal-effects analysis (Table 12) shows that the effect of income diversification on bank stability is conditional on the level of credit risk. At a low credit-risk level (CRISK = 0.01; 25th percentile), income diversification has a negative and significant effect on bank stability (dy/dx = -1.530; p = 0.025). However, when credit risk rises to a moderate level (CRISK = 0.03; median), the effect remains negative but is no longer statistically significant (dy/dx = -0.486; p = 0.472). At a high credit-risk level (CRISK = 0.05; 75th percentile), the effect of IDIV changes direction to positive (dy/dx = 0.556) but remains insignificant (p = 0.586).

This finding indicates that in banks with good asset quality (low credit risk), income diversification has the potential to generate inefficiency and agency costs that reduce stability (Stiroh & Rumble, 2006). Conversely, under higher credit-risk conditions, income diversification no longer has a negative effect, although it is not yet strong enough to function as a statistically significant buffering mechanism. This pattern shows that the benefits of income diversification begin to emerge when banks face credit pressure, but the effect is not yet optimal.

Meanwhile, at various levels of liquidity concentration (low, moderate, and high), the marginal effect of income diversification remains negative but statistically insignificant (p > 0.10). This result indicates that the structure of asset composition by liquidity category does not moderate the relationship between income diversification and bank stability, so the effect of income diversification on stability is relatively unaffected by banks' liquidity-concentration conditions in this study sample.

4.9 Discussion of Results and Hypothesis Testing

4.9.1 Hypothesis 1: Effect of Income Diversification on Bank Stability

Variable	Coefficient	Std. Err.	t-stat.	p-value
IDIV	-0.6928	0.6428	-1.08	0.288

The first hypothesis (H1) predicts that income diversification (IDIV) has a negative effect on the stability of conventional banks in Indonesia. The System GMM estimation results show that the IDIV coefficient is negative (β = -0.6928), but not statistically significant (p = 0.288). Thus, H1 is not supported.

This finding indicates that income diversification has not yet had a direct effect on bank stability. Although expansion into non-interest income sources has the potential to increase operational complexity and agency costs, its impact is not yet large enough to significantly affect the Z-Score. This result shows that banks in Indonesia are still able to absorb the initial consequences of diversification without experiencing a meaningful decline in stability, consistent with the findings of Meslier-Crouzille et al. (2013a).

The mean IDIV value of 0.2142 indicates that Indonesian banking is still at an early stage of income diversification. At this level, neither the benefits of diversification nor the costs it generates are strong enough to materially affect bank stability. This finding is consistent with Nguyen et al. (2021), who show that the benefits of diversification become optimal only after reaching a certain level. Therefore, the development of non-interest income still needs to be balanced with stronger risk-management capacity so that the benefits of diversification can be obtained without increasing bank-stability risk.

4.9.2 Hypothesis 2: Effect of Credit Risk on Bank Stability

Variable	Coefficient	Std. Err.	t-stat.	p-value
CRISK	-10.025	2.4819	-4.04	0,000***

The second hypothesis (H2) predicts that credit risk (CRISK) has a negative effect on the stability of conventional banks in Indonesia. The System GMM estimation results show that CRISK has a negative and significant effect ($\beta = -10.0250$; $p = 0.000$), so H2 is supported. Because BSTAB is specified as the natural logarithm of the Z-score, the coefficient $\beta = -10.025$ is interpreted as follows: an increase in CRISK of 0.01 (1 percentage point) is associated with a change in BSTAB of $-10.025 \times 0.01 = -0.10025$. Using the exact approach, %ΔZ-score = (e^{-0.10025} - 1) × 100% ≈ -9.54%. Thus, a 1-percentage-point increase in credit risk is associated with an approximately 9.5% decrease in the Z-score, ceteris paribus. The magnitude of this effect shows that credit risk has a relatively strong economic influence on banking stability.

This negative effect indicates that an increase in credit risk drives an increase in the formation of Allowance for Impairment Losses (CKPN), which depresses profitability and reduces capital capacity as a risk buffer, thereby lowering the Z-Score (Ariefianto et al., 2026). This mechanism becomes increasingly relevant during the pandemic and economic-recovery periods, when banking asset quality is under pressure.

This finding is consistent with the studies of Beck et al. (2022) and Fiordelisi et al. (2011), which place credit risk as a main determinant of banking stability. In the Indonesian context, this result also supports the policy of the Financial Services Authority (OJK), which prioritizes strengthening credit-risk management through POJK Number 18/POJK.03/2022 as an effort to maintain banking stability.

4.9.3 Hypothesis 3: Effect of Liquidity Concentration on Bank Stability

Variable	Coefficient	Std. Err.	t-stat.	p-value
LIQHHI	-0.3044	0.5002	-0.61	0.547

The third hypothesis (H3) predicts that liquidity concentration (LIQHHI) has a negative effect on bank stability. The System GMM estimation results show that the LIQHHI coefficient is negative ($\beta = -0.3044$), but not statistically significant ($p = 0.547$). Thus, H3 is not supported.

Although, theoretically, an excessively high concentration of assets in either liquid or illiquid assets can increase funding risk (Drehmann & Nikolaou, 2010), the results of this study show that variation in liquidity concentration has not had a material effect on bank stability. This finding indicates that conventional commercial banks in Indonesia are able to maintain liquidity concentration at a controlled level.

These results are consistent with the characteristics of Indonesian banking, which tends to maintain liquidity buffers above regulatory requirements (OJK, 2022). Therefore, changes in the composition of liquid assets do not develop into systemic risk capable of reducing bank stability (Lee et al., 2013).

4.9.4 Hypothesis 4: Effect of the Three-Way Interaction on Bank Stability

Variable	Coefficient	Std. Err.	t-stat.	p-value
IDIV_CRISK_c	52.1765	27.3523	1.91	0,064*
CRISK_LIQHHI_c	33.7905	6.8862	4.91	0,000***
IDIV_LIQHHI_c	1.775	3.061	0.58	0.566
IDIVxCRISKxLIQHHI_c	-55.6397	141.1338	-0.39	0.696

The fourth hypothesis is formulated as two competing hypotheses to test whether income diversification, credit risk, and liquidity concentration simultaneously form a *compounding* or *buffering* mechanism for bank stability. H4a predicts that the three-way interaction IDIV x CRISK x LIQHHI has a negative and significant effect on bank stability, whereas H4b predicts that the three-way interaction has a positive and significant effect on bank stability.

The H4a test results show that the three-way interaction among income diversification (IDIV), credit risk (CRISK), and liquidity concentration (LIQHHI) has a coefficient of −55.6397 with a p-value of 0.696. The results show that the three-way interaction is not statistically significant, so there is insufficient empirical evidence to support H4a. Although the interaction coefficient shows a negative direction that could theoretically indicate a *compounding* effect, the effect is not significantly different from zero. Therefore, the simultaneous presence of income diversification, credit risk, and liquidity concentration is not shown to significantly alter the relationship between income diversification and bank stability in this study sample.

The study results also do not support H4b because the three-way interaction among income diversification, credit risk, and liquidity concentration is not statistically significant ($\beta = -55.6397$; $p = 0.696$). Although the interaction between credit risk and liquidity concentration shows a positive and statistically significant coefficient ($\beta = 33.7905$; $p < 0.001$), this result is a two-way interaction and cannot be used as evidence to support the three-way moderation hypothesis. The significant CRISK × LIQHHI interaction indicates that the relationship between credit risk and bank stability differs at certain levels of liquidity concentration. Nevertheless, this finding does not prove that liquidity concentration significantly moderates the combined effect of income diversification and credit risk on bank stability. Therefore, H4b is declared unsupported.

The two-way interaction results show that the interaction between credit risk and liquidity concentration (CRISK × LIQHHI) has a positive coefficient of 33.7905 and is statistically significant ($p < 0.001$). This finding indicates that the relationship between credit risk and bank stability varies across different levels of liquidity concentration. However, this two-way interaction result cannot be used as evidence to support H4b, because H4b specifically tests the simultaneous three-way interaction among income diversification, credit risk, and liquidity concentration (IDIV × CRISK × LIQHHI). Thus, the CRISK × LIQHHI interaction is reported as an additional partial-interaction finding and is not interpreted as evidence of a buffering mechanism in the three-way interaction.

Overall, this study finds interactions in several pairs of variables, particularly CRISK × LIQHHI and IDIV × CRISK. However, no adequate statistical evidence is found for either the compounding or buffering mechanism at the three-way interaction level. The three-way interaction IDIV × CRISK × LIQHHI has a coefficient of −55.6397 with a p-value of 0.696, and is therefore not statistically significant. Accordingly, the results show that no simultaneous three-way interaction effect is statistically detected in the study sample and model specification. The non-significance of the three-way interaction cannot be interpreted as evidence that the three dimensions operate independently; rather, it indicates that the simultaneous three-way interaction mechanism has not received empirical support in this study.

4.10 Summary of Hypothesis Testing

The study finds that bank stability is more strongly influenced by credit risk than by income diversification (Table 13).

Table 13. Summary of Hypothesis Testing Results

H	Hypothesis Statement	Coefficient	p-value	Decision
H1	IDIV → BSTAB (negative)	−0.693	0.288	Not Supported
H2	CRISK → BSTAB (negative)	−10.025	0.000	Supported (1%)
H3	LIQHHI → BSTAB (negative)	−0.304	0.547	Not Supported
H4a	IDIV×CRISK×LIQHHI → BSTAB (negative, compounding)	−55.640	0.696	Not Supported
H4b	IDIV×CRISK×LIQHHI → BSTAB (positive, buffering)	−55.640	0.696	Not Supported
_	CRISKxLIQHHI→BSTAB (two-way interaction)	33.791	0.000	Significant at 1%
_	IDIVxCRISK→BSTAB (two-way interaction)	52.177	0.064	Significant at 10%

Note: Sig. 1% ($p < 0.01$); Sig. 10% ($p < 0.10$); Not Sig. ($p > 0.10$).

Source: Stata processing output (2026), bank panel data 2019-2025

Overall, the hypothesis-testing results (Table 13) show that credit risk (CRISK) is the main determinant of conventional bank stability in Indonesia. The second hypothesis (H2) is empirically supported (β = -10.025; $p < 0.01$), whereas the first hypothesis (H1) and the third hypothesis (H3) are not supported because income diversification (IDIV) and liquidity concentration (LIQHHI) do not have significant direct effects on bank stability.

For the fourth hypothesis (H4), the three-way interaction IDIV×CRISK×LIQHHI is not significant (β = -55.640; p = 0.696), so neither the compounding nor the buffering mechanism is empirically demonstrated. Thus, H4a and H4b are both unsupported by the data. The absence of a significant three-way coefficient indicates that no statistical evidence is found for the simultaneous effect of the three risk dimensions on bank stability in this study sample.

Nevertheless, the two-way interaction tests show partial findings that need to be reported. The CRISK×LIQHHI interaction has a positive and significant effect (β = 33.791; $p < 0.01$), while IDIV×CRISK is significant at the 10% level (β = 52.177; p = 0.064). These findings indicate that interactions among variables occur only partially, not simultaneously. It should be emphasized that these two-way interaction findings cannot be interpreted as support for H4b, because H4b specifically requires significance at the three-way interaction level, not the two-way level.

Thus, Indonesian banking stability is primarily influenced by credit risk, both directly and through its interaction with liquidity concentration and, to a weaker extent, with income diversification. In contrast, income diversification has not been able to form an effective protective mechanism through the three-way interaction. Therefore, strengthening banking stability needs to prioritize credit-risk control supported by liquidity management, while income diversification is positioned as a supporting strategy rather than the main risk-mitigation instrument.

5. Conclusion and Suggestions

This study analyzes the impact of income diversification (IDIV), credit risk (CRISK), and liquidity concentration (LIQHHI), as well as their interactions, on the stability of conventional commercial banks listed on the Indonesia Stock Exchange during the 2019–2025 period, using the Two-Step System GMM method. Estimation is conducted on a balanced panel consisting of 38 banks (228 effective observations) using mean-centered variables. The diagnostic-test results show that the model meets the validity criteria based on the Wald, Hansen, and AR(2) tests.

First, income diversification (IDIV) does not significantly affect bank stability ($\beta = -0.693$; $p = 0.288$). However, marginal-effects analysis shows that diversification has a significant negative impact when credit risk is low, while its effect becomes insignificant at higher levels of credit risk. This shows that the benefits of income diversification remain conditional and have not yet been optimized.

Second, credit risk (CRISK) is the main determinant of bank stability ($\beta = -10.025$; $p < 0.01$). Because BSTAB is measured as the natural logarithm of the Z-score, the coefficient indicates that every 1-percentage-point increase in CRISK is associated with an approximately 9.5% decrease in the Z-score. The magnitude of this effect shows that credit-asset quality has a strong economic role in influencing banking stability.

Third, liquidity concentration (LIQHHI) does not significantly affect bank stability ($\beta = -0.304$; $p = 0.547$). This finding shows that liquidity conditions in the Indonesian banking sector remained relatively controlled during the study period, meaning that liquidity concentration did not act as a direct driver of instability.

Fourth, the three-way interaction IDIV×CRISK×LIQHHI is not significant ($\beta = -55.640$; $p = 0.696$); consequently, no evidence is found of a simultaneous compounding or buffering mechanism. However, the two-way interaction analysis reveals that CRISK×LIQHHI has a positive and significant effect at the 1% level ($\beta = 33.791$; $p < 0.01$), while IDIV×CRISK is significant at the 10% level ($\beta = 52.177$; $p = 0.064$). These findings show that risk interactions occur partially, particularly between credit risk and liquidity concentration, but have not yet formed a three-way synergy that affects bank stability.

6. Limitations and Further Research

The sample coverage in this study is limited to conventional commercial banks listed on the Indonesia Stock Exchange (IDX), so the findings cannot be generalized to Rural Banks (BPR) or banks that are not listed on the capital market. Furthermore, the polynomial interaction variable (final VIF 1.62 after mean-centering) represents a structural limitation of the interaction model. Although it does not disqualify the validity of the *System GMM* estimation, this issue needs to be considered when interpreting the interaction coefficients.

The 2019–2025 observation period, which includes the COVID-19 pandemic conditions, may cause high structural heterogeneity across periods, potentially dampening systematic interaction patterns and reducing statistical detection power for moderation effects. In addition, the use of LIQHHI as an HHI-based asset-liquidity concentration index has not been widely explored in the Indonesian banking literature. Thus, empirical construct validation against standard liquidity measures commonly used by regulators and the main literature, such as the *Loan to Deposit Ratio* (LDR), *Liquidity Coverage Ratio* (LCR), or *Net Stable Funding Ratio* (NSFR), has not yet been conducted. The absence of a direct correlation test between LIQHHI and conventional proxies means that this indicator must be interpreted cautiously, while also creating an opportunity for future research to confirm the validity of the proxy measurement.

Based on these limitations, future research is advised to expand the sample size by including Islamic banks to test comparative models of income-diversification effects and risk interactions. A *threshold regression* or *smooth transition regression* (STR) approach can also be adopted to detect non-linear effects and income-diversification thresholds on stability, given that the mean IDIV value remains below the optimal threshold.

Further research is strongly recommended to integrate corporate-governance variables, such as board effectiveness and ownership structure, as additional moderating variables, given that managerial capacity is an absolute prerequisite for the effectiveness of diversification strategies. Finally, separate testing across sub-periods (pre-pandemic, pandemic, post-pandemic) can use a structural-change analysis approach to identify shifts in the timing of the determinants of banking stability resulting from extraordinary macroeconomic shocks beyond the pandemic period.

Declaration of the Use of AI and AI-Assisted Technologies in the Writing Process

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) as an assistive tool to improve language clarity, grammar, sentence editing, and consistency in academic writing. AI was not used to generate research data, perform statistical analyses, interpret research results, or draw scientific conclusions. After using the tool, the entire manuscript was reviewed, checked, and edited again by the authors. All authors take full responsibility for the accuracy, originality, and final content of the published manuscript.

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