BANKING HEALTH INDICATORS AND THEIR IMPACT ON CREDIT RISK IN THE INDONESIAN BANKING SECTOR

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Abstract

Credit risk is inherent in the banking sector, as banks extend credit to the public as a primary source of income. Banks supervised by the Financial Services Authority (Otoritas Jasa Keuangan, OJK) are required to prioritize prudential principles, leading the OJK to monitor risk management in banking through the Non-Performing Loan (NPL) ratio. Various factors can contribute to an increase in credit risk for banks. This study aims to analyze banking-related factors and macroeconomic factors that may influence credit risk. The independent variables related to banking include SIZE, ROA, liquidity, bank capital, and asset quality, while the macroeconomic variables include GDP growth, inflation rate, and unemployment rate. The study employs a panel data regression method with a sample of 42 conventional banks listed on the Indonesia Stock Exchange from 2019 to 2023. The results reveal that liquidity and asset quality have a significant positive impact on credit risk, whereas bank capital, GDP growth, inflation rate, and unemployment rate have a significant negative impact on credit risk. Meanwhile, firm size, profitability, and the OEI ratio do not significantly influence credit risk. This research provides insights for financial managers in managing credit risk while considering macroeconomic conditions when making decisions. Additionally, for investors, the findings offer valuable perspectives on the factors to consider when evaluating banking institutions for investment purposes.

Keywords: Macroeconomic, Banking Sector, Panel Data Regression, Credit Risk

INTRODUCTION

The disbursement of loans to the public constitutes the primary source of income for banks. Agency theory explains that bank managers are obligated to extend credit to the public to generate profits for shareholders and secure incentives for themselves. Banks with high levels of profitability, liquidity, and capital reserves tend to allocate more credit. Conversely, even banks in less favorable conditions are required to maintain credit distribution to ensure their survival and operational continuity (Abdeljawad et al. 2024). Consequently, the process of extending credit to the public necessitates a prudent approach, as the funds disbursed are sourced from public deposits. Banks, therefore, bear the responsibility of safeguarding these public funds while ensuring sustainable credit operations (Kurniawan et al, 2022).

Risk is an inherent element of any event. In the banking sector, credit risk represents one of the primary risks faced by financial institutions (Saputra, 2023). Despite the significant challenges posed by credit risk, banks are required to continue extending loans due to market imperfections. Credit risk is defined as the potential failure of borrowers to fulfill their contractual obligations as agreed (Abdeljawad et al., 2024).

In Indonesia, banks are regulated and supervised by the Financial Services Authority (Otoritas Jasa Keuangan or OJK), which mandates adherence to prudential principles and effective risk management in banking operations. The Non-Performing Loan (NPL) ratio is a key indicator used to assess credit risk within the banking system of a country. Weak credit approval procedures, inadequate risk assessment capabilities, and unfavorable economic conditions are among the factors contributing to high NPL levels (Suhardono et al. 2023). According to statistical data from OJK, the NPL ratio in Indonesian banking experienced an increase during the 2020–2022 period, exceeding 3% of the total loans disbursed. However, this trend showed improvement by September 2024, with the NPL ratio declining to 2.21%. The inability of banks to ensure smooth loan repayments adversely impacts profitability, leading to higher provisioning requirements (Yilmaz Kucuk 2022).

This study aims to analyze the factors influencing credit risk in banking companies listed on the Indonesia Stock Exchange (IDX). The research seeks to explain the impact of banking indicators and external factors on credit risk. Analyzing these influencing factors has attracted significant interest among researchers. For instance, liquidity has been found to have a positive effect on credit risk (Trinh and Quan Ai Truong Tran 2024). Banks with higher liquidity tend to allocate more funds, thereby increasing exposure to greater risks (Abdeljawad et al. 2024). Similarly, profitability, as highlighted in the findings of (Dang et al. 2024), shows a negative correlation with credit risk. The higher a bank's profitability, the lower its credit risk tends to be. This study contributes to the ongoing discourse by exploring the relationships between banking-specific indicators, macroeconomic factors, and credit risk, providing deeper insights into risk management strategies for the Indonesian banking sector.

In addition to the evaluated indicators, macroeconomic factors, such as GDP, also negatively influence credit risk in the banking industry (Abdeljawad et al. 2024). GDP growth, reflecting the economic progress of a country, has a negative correlation with credit risk (Dang et al. 2024). Similarly, inflation and unemployment rates impact borrowers' repayment capacity and purchasing power, exerting a negative influence on credit risk in the banking sector (Abdeljawad et al. 2024). In this context, banks tend to adopt a more selective approach in loan disbursement, leading to lower credit risk levels.

Moreover, a bank's performance can also be measured by its efficiency level, as indicated by the Operating Expense to Operating Income (OEI) ratio. Currently, numerous banking institutions are embracing digital transformation, driving them to compete in achieving operational efficiency. Consequently, efficiency levels have emerged as a critical factor in assessing corporate credit risk. Banks with lower OEI ratios are generally associated with lower risk levels, highlighting their ability to manage risks effectively (Salas et al. 2024).

Based on the discussion, this study focuses on analyzing banking indicators and macroeconomic indicators to assess their influence on credit risk in banking companies in Indonesia. This research aims to make a significant contribution to understanding the dynamics of banking, particularly in decision-making processes that can impact credit risk.

REVIEW OF LITERATURE

Size

The study conducted by Abdeljawad et al. (2024) revealed that firm size has a significant negative effect on credit risk. Conversely, a different conclusion was presented by Astrini, Suwendra, and Suwarna (2018), who argued that larger firms tend to face higher credit risk. This finding aligns with the research of Al-Qudah et al. (2023).

Profitability

According to Abdeljawad et al. (2024), profitability levels have a significant negative effect on credit risk. This finding is consistent with the study by Yilmaz Kucuk (2022), which also highlighted that profitability negatively impacts credit risk. Similarly, Dang et al. (2024) reported that credit risk is negatively influenced by profitability, as measured in their study using Return on Assets (ROA).

Liquidity

Abdeljawad et al. (2024) revealed that liquidity has a significant positive effect on credit risk. Similarly, Trinh and Quan Ai Truong Tran (2024), in their related study, also found that liquidity positively influences credit risk. These findings are consistent with the study by Yudaruddin et al. (2024), which demonstrated that liquidity exerts a significant positive effect on credit risk.

Capital Adequacy Ratio

Yilmaz Kucuk (2022) highlighted that bank capital, measured through the Capital Adequacy Ratio (CAR), has a significant negative effect on credit risk, suggesting that effective credit risk management can be achieved with better capital adequacy. Similarly, Dang et al. (2024) also reported that capital exerts a significant negative influence on credit risk. In contrast, a study by Le and Pham (2021) presented an opposing view, stating that higher capital levels have a positive effect on credit risk, as larger capital reserves provide greater flexibility to undertake additional risks.

Asset Quality

Abdeljawad et al. (2024) revealed that asset quality has a significant positive effect on credit risk. In this context, asset quality is measured by the Loan Loss Provision ratio, indicating that higher provisioning levels are associated with increased credit risk. Similarly, Yilmaz Kucuk (2022) found that deteriorating asset quality significantly increases credit risk. However, Jasman and Murwaningsari (2022) presented contrasting findings, suggesting that higher asset quality reduces credit risk. This outcome reflects the ability of banks to adequately allocate reserves for potential loan losses, thereby mitigating credit risk.

Operational Efficiency (OEI)

The study conducted by Salas et al. (2024) revealed that the Operational Efficiency Indicator (OEI) has a significant positive effect on credit risk. Consistent with this finding, Azhar and Yeniwati (2020) demonstrated that banks with lower OEI levels, indicating better efficiency, experience lower credit risk, suggesting a positive relationship between efficient management and reduced credit risk. Similarly, the research by Asyadiah and Hasanuh (2023) indicated that as OEI decreases, credit risk diminishes, reflecting more efficient bank management. These findings align with Khan, Siddique, and Sarwar (2020), who asserted that higher operational efficiency reduces credit risk levels.

Gross Domestic Product

According to Abdeljawad et al. (2024), Gross Domestic Product (GDP) in the Middle East and North Africa (MENA) region has a significant negative effect on credit risk. This finding is consistent with the study by Dang et al. (2024), which also reported a significant negative relationship between GDP and credit risk in Vietnam, indicating that higher GDP levels reduce credit risk. However, a contrasting perspective was offered by Artenisa and Hyrije (2023). Their research focused on the Western Balkans (including Albania, Bosnia and Herzegovina, Croatia, Montenegro, North Macedonia, Serbia, and Kosovo) and found that increased GDP levels lead to higher credit risk. They argued that higher GDP stimulates greater lending activity, thereby elevating credit risk in these regions.

Inflation Rate

Abdeljawad et al. (2024) revealed that inflation rates in the Middle East and North Africa (MENA) region have a significant negative effect on credit risk. Similarly, Dang et al. (2024) found that inflation in Vietnam also exerts a significant negative influence on credit risk. Consistent with these findings, Artenisa and Hyrije (2023) demonstrated that inflation rates in the Western Balkans similarly have a significant negative effect on credit risk, suggesting a broader trend across diverse regions where higher inflation correlates with reduced credit risk levels.

Unemployment Rate

Artenisa and Hyrije (2023) highlighted that unemployment rates in the Western Balkans positively correlate with credit risk. Similarly, Patiu and De La (2024) found that unemployment rates in Southeast Asia significantly increase credit risk, demonstrating a positive and significant relationship. These findings are consistent with the study by Lee et al. (2020), which revealed that unemployment rates in the European Union also exhibit a significant positive correlation with credit risk, indicating a common pattern across regions where higher unemployment rates lead to elevated credit risk.

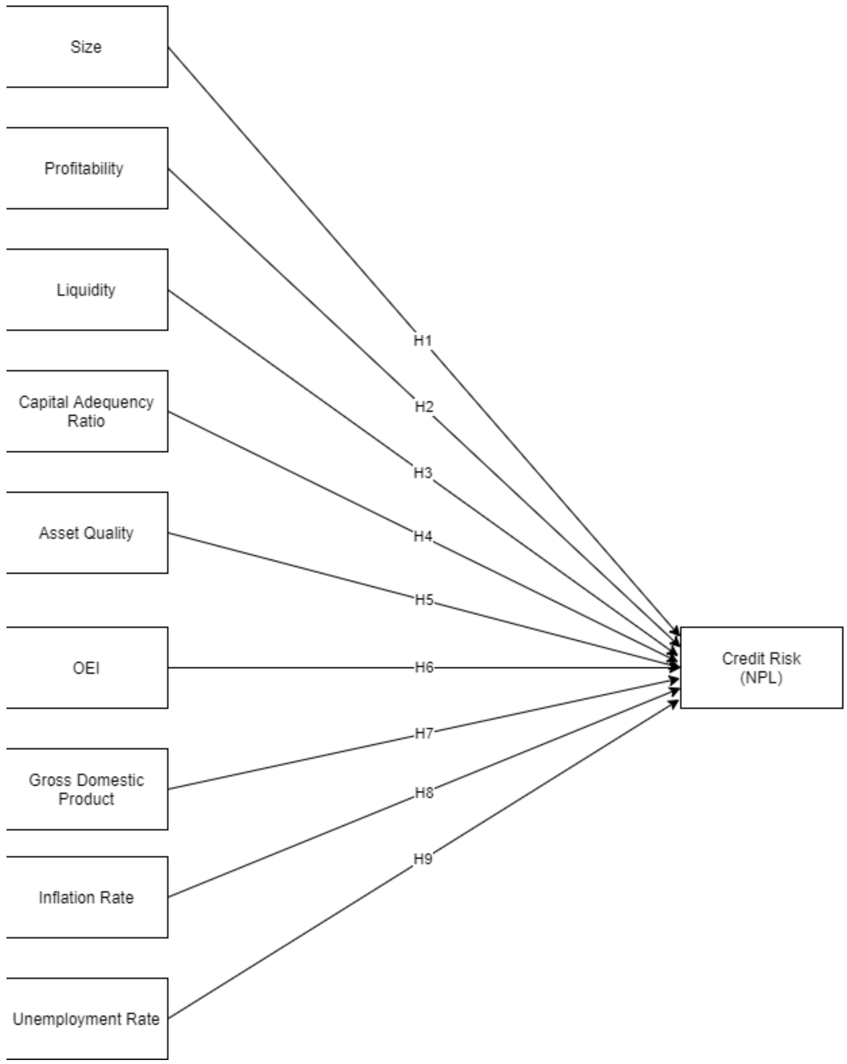

Figure 1.

Research Framework

RESEARCH METHOD

This study, with a population consisting of banks in Indonesia, uses quantitative data obtained from the Indonesia Stock Exchange (IDX), financial reports and annual reports of each company, the BPS website, and data from the Bank Indonesia website. The research employs the Purposive Sampling method for data collection, chosen because it focuses on specific objectives. The study is conducted on banking companies that meet the established criteria. The criteria used in this study are as follows:

1. Banking companies listed on the Indonesia Stock Exchange in 2023.
2. Banking companies with complete variable data are required for this study.
3. Banking companies that do not operate entirely based on Sharia principles.

Table 1.
Sample Selection Criteria

Description	Amount
Banking companies listed on the Indonesia Stock Exchange in 2023.	**47**
Islamic banks listed on the Indonesia Stock Exchange.	**(4)**
The number of banks with incomplete data.	**(1)**
Eligible companies to be included as samples.	**42**

Source: Data Processing (2024)

The data analysis in this study includes descriptive statistics, panel data regression analysis, regression model estimation, and model selection. To evaluate the effectiveness of the regression model, the next step involves conducting classical assumption tests. If the results of the classical assumption tests are positive, the researcher proceeds with partial tests (T-tests) and simultaneous tests (F-tests) to address the research hypotheses. Additionally, the researcher conducts a coefficient of determination test to assess the extent to which the model can explain the overall fluctuations of the independent variables within the model.
The regression model used in this study is presented as follows::

$$NPL = \beta_0 + \beta_1 Size_{it} + \beta_2\, ROA_{it} + \beta_3 Liq_{it} + \beta_4\, CAR_{it} + \beta_5 ASQ_{it} + \beta_6\, OEI_{it} + \beta_7 GDP_{it} + \beta_8 INF_{it} + \beta_9\, UNEMP_{it} + \epsilon_{it}$$

RESULTS AND DISCUSSION

Descriptive Statistical Analysis

According to Sekaran and Bougie (2016), descriptive analysis is used to summarize, describe, and understand the distribution, trends, and patterns of data clearly before further analysis. The results of the descriptive statistical analysis are presented in the following table.

Table 2.
Descriptive Statistic

Variable	Mean	Maximum	Minimum	Std. Dev.	Observations
NPL	0.03397	0.2227	0	0.02686	210
SIZE	13.66628	15.3373	12.12092	0.74332	210
ROA	0.00323	0.0414	-0.18058	0.02418	210
LIQ	0.80758	2.5294	0.11983	0.27849	210
CAR	0.20041	0.81937	0.00017	0.12638	210
ASQ	0.03917	0.27679	0.00001	0.03622	210
OEI	0.99073	6.44496	0.42552	0.57907	210
GDP	0.034	0.0531	-0.0207	0.028	210
INF	0.02878	0.0551	0.0168	0.0138	210
UNEMP	0.05743	0.06375	0.05105	0.00451	210

Source: Data Processing (2024)

Based on the results of the descriptive statistical analysis, the research data shows various patterns that are relevant to supporting further analysis. The Non-Performing Loan (NPL) ratio has an average of 3.40% with a maximum value reaching 22.27%, reflecting significant credit risk in certain banks. Firm size (SIZE) has an average value of 13.67 with moderate variation, indicating the dominance of large banks in the sample. Return on Assets (ROA) has a low average of 0.32%, with a minimum value of -18.06%, which indicates that some banks experienced losses during the research period. The liquidity ratio (LIQ) averages 80.76%, demonstrating the banks' ability to meet short-term obligations, although there are banks with very high liquidity levels of up to 252.94%. Bank capital or the capital adequacy ratio (CAR) has an average of 20.04% with a standard deviation of 12.64%, reflecting that most banks have sufficient capital to cover risks. In addition, stable inflation at an average of 2.88% and an unemployment rate of 5.74% indicate supportive economic conditions. Overall, these data provide a comprehensive overview for exploring the relationship between financial and macroeconomic indicators on credit risk in the banking sector.

Panel Data Model Selection

In the study conducted by Fariska and Khaerunisa (2024), it was revealed that the Chow test and Hausman test are required to perform regression testing. The following are the results of the panel data model used in this study.

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Chow Test

This test is conducted to identify the most appropriate model through a comparison between the Common Effect model and the Fixed Effect model. The hypotheses for this test are formulated as follows: H0 states that the Common Effect model is more appropriate, which is indicated by a p-value > 0.05, whereas H1 states that the Fixed Effect model is more appropriate, which is shown by a p-value < 0.05. The application of the Chow test provides insights into the suitable model for this study so that the analysis conducted becomes more informative and precise.

Table 3.
Chow Test

Effect Test	**Statistic**	**d.f.**	**Prob.**
Cross-Section F	4.676948	(41,159)	0.0000
Cross-Section Chi-Square	166.148501	41	0.0000

Source: Data Processing (2024)

It can be seen in Table 3 above that the probability value of 0.000 is smaller than the threshold of 0.05. Therefore, the decision is made to reject the null hypothesis (H0) based on the conclusion that the Fixed Effect model is more appropriate compared to the Common Effect model.

Hausman Test

In the context of selecting the most appropriate panel data regression model for this research, the Hausman test plays a crucial role. This test aims to compare the Fixed Effect model with the Random Effect model. By using a Chi-square distribution, the Hausman test evaluates the suitability of each model. This study applies specific criteria for model selection, where H0 states that the Random Effect model is more appropriate, as indicated by a p-value > 0.05. Conversely, H1 states that the Fixed Effect model is more appropriate, as shown by a p-value < 0.05. Thus, the Hausman test contributes to determining the optimal model, enhancing the precision and reliability of panel data regression analysis in this research.

Table 4.
Hausman Test

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-Section Random	0.000000	9	1.0000

Source: Data Processing (2024)

As presented in Table 4, the Chi-Square Statistic value of 0.0000 indicates an invalid result, implying that the cross-section Chi-Square value of 0.0000 is less than 0.05. This means the null hypothesis (H0) is rejected, and the alternative hypothesis (Ha) is accepted. Consequently, the model selected based on the Hausman test is the Fixed Effect Model. Given the selection of the Fixed Effect Model, conducting the Lagrange Multiplier test is no longer necessary.

F-Test (Simultaneous Test)

To determine how significant the regression model is simultaneously, the F-test (Simultaneous Test) is conducted. The probability value, also referred to as the F-statistic, must be smaller than 0.05 to indicate that there is a significant effect between the independent variables and the dependent variable. The summary table of the simultaneous test (F-test) conducted in this study can be seen below.

Table 5.
F-Test

R Squared	Model Summary Adjusted R-Squared	F-Statistic	Prob (F-Statistic)
0.839297	0.788762	16.60811	0.00000

Source: Data Processing (2024)

Based on the results in Table 5, the F-statistic value of 0.00000 < 0.05 indicates that H0 is rejected and H1 is accepted, meaning that there is a significant simultaneous effect between the independent variables and the dependent variable.

Panel Data Regression Model

According to Fariska and Khaerunisa (2024), regression data analysis is a combination of data that represents a specific period and cross-sectional data, which are arranged by incorporating relevant variables from both types of data into an information model. Panel data can significantly reduce issues related to omitted variables.

This study employs panel data regression using the Fixed Effect Model. The selection of this model is based on the model tests previously conducted. The results of the panel data regression analysis can be seen as follows.

Table 6.
Panel Data Regression Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.234218	0.111111	2.107969	0.0366
SIZE	-0.000461	0.010848	-0.042477	0.9662
ROA	-0.084099	0.092720	-0.907018	0.3658
LIQ	0.012900	0.004490	2.873198	0.0046**
CAR	-0.005744	0.002397	-2.396128	0.0177**
ASQ	0.327470	0.044790	7.311280	0.0000**
OEI	0.000762	0.001603	0.475481	0.6351
GDP	-0.959995	0.175023	-5.484978	0.0000**
INF	-1.665711	0.332086	-5.015905	0.0000**
UNEMP	-2.367258	0.509097	-4.649916	0.0000**

*α = 10% **α = 5%

Source: Data Processing (2024)

Based on the regression data above, the results are as follows:

1. The study posits that size influences credit risk (NPL). The coefficient in the table shows a value of -0.000461, which is less than 0, indicating a negative relationship between size and credit risk. However, the probability value for size is 0.9662, which exceeds the significance level of α = 0.05. Therefore, size does not have a statistically significant effect on credit risk.
2. The study hypothesizes that ROA influences credit risk (NPL). The coefficient result is -0.084099, which is less than 0, indicating a negative relationship between ROA and credit risk. However, the probability value for ROA is 0.3658, which is greater than α = 0.05. Thus, ROA does not have a statistically significant effect on credit risk.
3. The results indicate that liquidity (Liq) influences credit risk (NPL). The coefficient result shows a value of 0.012900, which is greater than 0, suggesting a positive

relationship between liquidity and credit risk. The probability value for Liq is 0.0046, which is less than $\alpha = 0.05$. Therefore, liquidity significantly influences credit risk, with a positive coefficient direction.

4. The analysis suggests that bank capital (CAR) influences credit risk (NPL). The coefficient value is -0.005744, which is less than 0, indicating a negative relationship between CAR and credit risk. The probability value for CAR is 0.0177, which is less than $\alpha = 0.05$. Consequently, CAR significantly influences credit risk, with a negative coefficient direction.
5. The findings reveal that asset quality (ASQ) influences credit risk (NPL). The coefficient result is 0.327470, which is greater than 0, indicating a positive relationship between asset quality and credit risk. The probability value for ASQ is 0.0000, which is less than $\alpha = 0.05$. Therefore, asset quality significantly influences credit risk, with a positive coefficient direction.
6. The results suggest that the Operating Expense to Operating Income Ratio (OEI) influences credit risk (NPL). The coefficient value is 0.000762, which is greater than 0, indicating a positive relationship between OEI and credit risk. However, the probability value for OEI is 0.6351, which exceeds $\alpha = 0.05$. Thus, OEI does not significantly influence credit risk.
7. The analysis indicates that GDP influences credit risk (NPL). The coefficient result is -0.959995, which is less than 0, signifying a negative relationship between GDP and credit risk. The probability value for GDP is 0.0000, which is less than $\alpha = 0.05$. Hence, GDP significantly influences credit risk, with a negative coefficient direction.
8. The findings confirm that inflation (INF) influences credit risk (NPL). The coefficient value is -1.665711, which is less than 0, indicating a negative relationship between inflation and credit risk. The probability value for inflation is 0.0000, which is less than $\alpha = 0.05$. Therefore, inflation significantly influences credit risk, with a negative coefficient direction.
9. The results demonstrate that unemployment (UNEMP) influences credit risk (NPL). The coefficient value is -2.367258, which is less than 0, indicating a negative relationship between unemployment and credit risk. The probability value for unemployment is

0.0000, which is less than α = 0.05. Consequently, unemployment significantly influences credit risk, with a negative coefficient direction.

Size to Credit Risk

The test results show that size and NPL have a negative direction. This result aligns with the study by Abdeljawad et al. (2024), which indicates that larger banking companies have better risk diversification capacity and economies of scale. However, the probability value of 0.9662, which is greater than α (0.05), indicates that there is no significant influence between size and NPL. This result demonstrates that bank size does not have a relationship with credit risk management measured by NPL. This reflects the varying complexity of bank management, as bank size does not necessarily represent better risk management compared to smaller banks (Al-Qudah et al. 2023). Credit risk management in banking is not influenced by the size of the bank.

Profitability to Credit Risk

The test results indicate that profitability (ROA) and NPL have a negative direction, meaning higher profitability reflects more effective credit management, enabling banks to reduce non-performing loans (Abdeljawad et al. 2024). However, the probability value of 0.3658, which is greater than α (0.05), shows no significant influence between ROA and NPL. Banks with higher profitability might allocate larger reserves for credit risk but may also employ different risk strategies, which do not directly affect credit management (Abdeljawad et al. 2024). High profitability may expose banks to higher credit risk if adequate risk management measures are not implemented (Yudaruddin et al. 2024). Hence, bank profitability does not influence credit risk strategies.

Liquidity to Credit Risk

Liquidity has a significant positive relationship with credit risk, with a probability value of 0.0046, which is smaller than α (0.05). This result aligns with (Abdeljawad et al. 2024), which reveals that banks with high liquidity tend to face moral hazard, as the availability of funds may encourage more aggressive lending practices. Excess liquidity may drive riskier behaviors, including less selective lending (Yudaruddin et al. 2024), thereby increasing credit risk in banking.

Capital Adequacy Ratio to Credit Risk

The Capital Adequacy Ratio (CAR) has a significant positive relationship with a probability value of 0.0177, smaller than α (0.05), with a negative coefficient direction. This result supports the study by Dang et al. (2024), which states that a higher CAR indicates the bank's ability to absorb losses from non-performing loans. Higher capital reduces reliance on costly external funding, lowering credit portfolio pressure and minimizing credit risk (Le and Pham 2021). Banks with higher capital can better absorb losses from problematic loans (Yilmaz Kucuk 2022).

Asset Quality to Credit Risk

Asset Quality (ASQ) has a significant positive relationship, with a probability value of 0.0000, smaller than α (0.05), and a positive correlation direction. This result is consistent with (Abdeljawad et al. 2024), which shows that higher loan provisioning increases credit risk. Poor asset quality directly increases credit risk as banks must allocate larger reserves for loan losses, worsening financial burdens (Yilmaz Kucuk 2022). Asset quality reflects the quality of assets managed by banks, and deterioration increases credit risk due to inefficiencies in credit risk management (Jasman and Murwaningsari 2022).

Operational Efficiency to Credit Risk

Operational Efficiency (OEI) has a positive correlation with credit risk (NPL) but a probability value of 0.6351, greater than α (0.05). This indicates that operational efficiency is not always significant for NPL because bank efficiency can be influenced by broader macroeconomic contexts and credit policies (Salas et al. 2024). Efficiency levels do not always directly reflect credit risk, as NPL is often influenced by strategic decisions made by banks (Asyadiah and Hasanuh 2023).

Gross Domestic Product (GDP)

GDP growth has a significant negative relationship with a probability value of 0.0000, smaller than α (0.05). Higher GDP growth reduces credit risk as it increases societal income, improving loan repayment capacity and directly lowering non-performing loans (Abdeljawad et al. 2024). This result is also consistent with Dang et al. (2024), which states that GDP growth contributes to economic stability, enhancing borrowers' ability to fulfill credit obligations. As GDP increases, economic stability grows, improving confidence in the banking sector and reducing credit risk (Artenisa and Hyrije 2023).

Inflation Rate

Inflation has a significant negative correlation, with a probability value of 0.0000, smaller than α (0.05). This result aligns with Dang et al. (2024), which indicates that high inflation prompts banks to lend to more stable sectors, reducing default risk. During periods of high inflation, banks tend to tighten credit standards (Abdeljawad et al. 2024) to mitigate problematic loans and reduce credit risk.

Unemployment Rate

The unemployment rate has a significant negative correlation, with a probability value of 0.0000, smaller than α (0.05). This result contrasts with studies by Artenisa and Hyrije (2023) and Patiu and De La (2024), which suggests a positive correlation between unemployment and credit risk. However, it can be understood that high unemployment reflects low economic growth. In such conditions, banks tend to implement stricter borrower selection, reducing credit risk levels.

Goodness of Fit Test

This test is conducted to determine the extent to which the independent variables collectively influence the dependent variable in the regression model. The test provides an overview of the simultaneous relationship between the variables. The results of this test help explain the variation in the dependent variable, demonstrating the overall explanatory power of the regression model.

Table 7.
Goodness of Fit Test

R Squared	Model Summary Adjusted R-Squared	F-Statistic	Prob (F-Statistic)
0.839297	0.788762	16.60811	0.00000

Source: Data Processing (2024)

Based on the table above, it can be seen that the Adjusted R-squared value is 78.78%, indicating that the independent variables—firm size, profitability, liquidity, bank capital, asset quality, operational efficiency (OEI), GDP growth, inflation rate, and unemployment rate—simultaneously explain 78.78% of the variation in credit risk, while the remaining 21.22% is influenced by other factors outside this study.

CONCLUSION

One of the primary sources of income for banks is providing credit to the public. However, this activity is inherently associated with risks, requiring banks to prioritize prudential principles when extending credit. Banking companies in Indonesia are supervised by the Financial Services Authority (OJK), making risk management processes a crucial aspect for banks to prioritize. This study examines factors influencing credit risk, including firm size, profitability, liquidity, bank capital, asset quality, and the OEI ratio. Additionally, macroeconomic variables such as GDP growth, inflation, and unemployment rates are included as potential factors affecting credit risk. The partial test results of this study indicate that liquidity, bank capital, asset quality, GDP growth, inflation, and unemployment rates have significant effects on credit risk. Meanwhile, firm size, profitability, and the OEI ratio do not significantly influence credit risk. This is because each bank adopts its own credit risk management strategies, making firm size less relevant in determining risk management effectiveness. Similarly, profitability levels, while potentially indicative of higher reserves, do not directly impact risk control strategies. The same applies to the OEI ratio, which represents efficiency but often has less impact on credit risk than strategic decisions. In this study, the independent variables—firm size, profitability, liquidity, bank capital, asset quality, the OEI ratio, GDP growth, inflation, and unemployment rates—collectively influence credit risk. Future research could refine the sample data specifications and include additional independent variables, such as leverage ratios or other macroeconomic variables like Bank Indonesia's interest rate or foreign exchange rates.

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