Asian Economic and Financial Review
ISSN(e): 2222-6737
ISSN(p): 2305-2147
DOI: 10.55493/5002.v14i3.5014
Vol. 14, No. 3, 191-207.

URL: www.aessweb.com

The dynamic relationships of credit risk, profitability, and capital: Evidence from Indonesia

Hendra Sutanto[1+]
Meiryani[2]
Moch. Doddy Ariefianto[3]

[1]*Accounting Department, Binus Graduate Program, Master of Accounting, Bina Nusantara University, Jakarta, 11480, Indonesia.*
Email: Hendra.sutanto001@binus.ac.id
[2]*Accounting Program Department, School of Accounting, Bina Nusantara University, Jakarta, 11480, Indonesia.*
Email: Meiryani001@binus.ac.id
[3]*Finance Program Accounting Department, School of Accounting, Bina Nusantara University, Jakarta, 11480, Indonesia.*
Email: doddy.areifianto@binus.edu

(+ Corresponding author)

Article History
Received: 18 August 2023
Revised: 19 October 2023
Accepted: 26 January 2024
Published: 15 March 2024

Keywords
Capital
COVID-19
Credit risk
Dynamic relationship
Econometrics
Financial model
Profitability.

JEL Classification:
C23; G21; G28; G32.

ABSTRACT

The study examines the dynamic relationships between credit risk, profitability, and capital. Credit risk is a crucial metric for bank health, affecting micro- and macro-financial stability. It is impossible to overstate the importance of effective risk management procedures for maintaining the health and stability of banks and reducing the potential threat that non-performing loans may pose. Profitability and capital, being of paramount importance in the realm of credit risk, represent intricately linked factors. While existing studies address the static linkages between credit risk, profitability, and capital in depth, there is a significant gap in our knowledge of their dynamic interactions. There exists a conspicuous void in our understanding of their dynamic interactions. To bridge this knowledge gap, our study employs a novel technique. We employ a Dynamic Common Correlated Effects (DCCE) model, leveraging a panel dataset encompassing 85 Indonesian banks, encompassing data spanning from January 2012 to September 2021. The study found that non-performing loans (NPLs) have a negative dynamic (and significant) relationship with profitability in the long run and short run, whereas capital is statistically unimportant. The equilibrating process of this dynamic relationship takes between 2.11 and 3.73 months. Our result is robust when examined across bank types but slightly different between before and during the COVID-19 era. The study contributes to understanding the relationships among credit risk, profitability, and the capital equilibrating process, and it has important implications for business practices and regulations, particularly in terms of financial stability.

Contribution/Originality: This study contributes to existing literature by examining the dynamic relationships with equilibrium processes in the pre- and COVID-19 eras. Utilizing a panel error correction mechanism, it specifically investigates the determinants of bank performance across diverse ownership structures in a country characterized by a predominantly small financial sector.

1. INTRODUCTION

Credit risk is a significant danger that can undoubtedly devastate the banking industry (Naili & Lahrichi, 2022). However, increased risk can result in larger profits, and the two are directly proportional. As risk increases, so does potential profit (Buchory, 2015). Credit risk (NPL_R) has been closely linked to financial performance because it has the potential to affect a bank's financial health, which can then affect the stability of a country's economy (Phung, Van Vu, & Tran, 2022). The existing literature has generally acknowledged the relationship between non-performing loan (NPLs) and their two main drivers, namely, profitability and capital (Phung et al., 2022; Zhu, Wang, & Wu, 2015). Financial organizations typically aim to maximize profits and maintain profitability. *Profitability* measures the bank's ability to generate earnings from its core business activities, whereas *capital* measures the amount of equity and reserves that the bank holds to absorb potential losses. This is achieved when banks earn money at lower rates while allowing investors and customers to borrow at higher rates, leading to increased profitability. However, if loans are not repaid, profitability will decrease.

A bank's loan portfolio affects the financial health and viability of the bank. Loan losses may not only mean plunging stock prices, but they can also spell trouble for top management at banks. It is well known that poorer corporate performance often precipitates a higher probability of executive turnover. The performance of a bank's loan portfolio often determines its financial performance. Agency theory predicts that the ownership form has a significant effect on the incentives and operating efficiency of firms (Greenbaum, Thakor, & Boot, 2019). There have been many studies on bank profitability, but not as many on credit risk, especially in terms of the time equilibration process in internal bank factors or macroeconomic conditions. Previous studies have focused on the correlation between credit risk and profitability, liquidity, and capital using panel data techniques to analyze time series data in various regions, such as Africa (Ozili, 2015) and South Asia (Islam & Nishiyama, 2016) as well as in the context of Asian commercial banks (Lee & Hsieh, 2013). Only a few studies have utilized dynamic panel methods to analyze the factors affecting bank's profitability (Abbas, Iqbal, & Aziz, 2019; Ozili, 2017). A static approach assumes that the relationships between variables are constant over time and does not account for changes in these relationships.

To fill in the gaps in the research, we create a dynamic econometric model to look at how credit risk, profitability, and capital are related in the banking industry. The model uses a panel of data with a lot of observations across different time periods and cross-sectional units. This model allows us to capture the time-varying nature of the relationships between variables and make more accurate predictions. The study uses a monthly panel dataset of 85 Indonesian banks, with data from January 2012 to September 2021. This method lets researchers find out how long it takes for changes in internal bank factors or macroeconomic conditions to have an effect on the banks. It also helps them understand long-term relationships and how errors are fixed. The report concludes with observations on the necessity of tightening banking regulations and maintaining oversight. The COVID-19 pandemic has introduced additional macroeconomic variables that may affect credit risk and the financial health of banks, and the study takes these factors into account, including the impact of government interventions such as fiscal stimulus packages and monetary policy measures (Kasinger et al., 2021; Pieter, 2021). The study also contributes to the field by utilizing a novel approach known as the dynamic common correlation effect (DCCE) approach. It takes into account cross-sectional unit dependence, a problem that the most recent panel techniques overlooked (Ariefianto, Trinugroho, Lau, & Sergi, 2022; Widjaja & Ariefianto, 2022).

Using Indonesia as the subject of this research is important because the country's banking industry has a unique history and ownership structure; thus, the research can provide insights that are relevant not only for Indonesia but also for other developing countries with similar economic and financial characteristics. The study can help in short-term management risk arrangements for internal risk variables, including the profitability, liquidity, capital, and size of the bank, as well as changes in interest rates, to ensure the health and stability of banks and mitigate the risk of bad debts (NPLs).

One of the key findings is that NPLs have a negative relationship with profitability, both in the short and long run, whereas capital was found to be statistically unimportant. This suggests that managing credit risk is crucial for maintaining a bank's profitability.

Furthermore, our study found that the process of credit risk equilibration takes between 2.11 and 3.73 months, which is a significant finding for bank managers who need to make timely decisions to mitigate risk. In addition, all internal bank variables, such as profitability, capital, and size, were found to significantly affect the short run, whereas only interest rates in the macroeconomic environment had a significant effect. This highlights the importance of internal bank management for ensuring financial stability.

Our research aimed to examine the robustness of the relationship between NPLs, profitability, and capital across different types of banks. Our sample included private and foreign banks, as well as state-owned banks. The results showed that private and foreign banks had the same outcome in the short run, whereas state bank capital and size were found to have a significant effect. These findings suggest that different types of banks may have different approaches to managing credit risk and profitability.

These results were robust across different types of banks, indicating that our findings are applicable across the banking industry. In addition, our study found that there were slight differences in the dynamic relationship between the variables before and during the COVID-19 era. Despite the pandemic's economic shock, NPL continued to have a negative impact on profitability. This finding is important for policymakers and bank managers, who need to navigate the challenging economic conditions brought about by the pandemic.

Overall, our research has significant implications for the banking industry and offers valuable insights for bank managers and policymakers on effectively managing credit risk and sustaining profitability in a dynamic economic environment. The structure of the remainder of the paper is as follows: Section 2 provides a comprehensive literature review and develops hypotheses. Section 3 elaborates on the research methodology, while Section 4 analyzes the obtained results. Finally, the concluding section 5 summarizes the findings and provides recommendations for future research endeavors.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

According to previous studies conducted in many countries, profitability and capital are among the most important factors behind credit risk (Saleh & Abu Afifa, 2020). Profitability is a crucial metric that investors use to evaluate a company's financial performance (Kimball, 1998) and it measures the efficiency of an organization in generating profits from its operations. High profitability is a sign of good management practices within an organization. Capital, in contrast, can help bolster business efforts and create better performance. It is obtained from both internal and external sources and provides an opportunity to set a higher standard in any business establishment (Haris, Ghozali, & Najmudin, 2022).

Therefore, to mitigate this risk, banks must maintain sufficient levels of equity to avoid capital risks. Equity acts as a buffer against potential losses and helps the bank cover any potential losses in the case of NPLs. However, increasing equity levels can decrease returns because the average cost of equity normally exceeds the cost of debt; in turn, this can reduce profitability (Al-Homaidi, Tabash, Farhan, & Almaqtari, 2018; Berger & Bouwman, 2013).

Several researchers have proposed theories forecasting the effect of profitability and capital on credit risk as either positive or negative (Saleh & Abu Afifa, 2020). The above argument suggests that greater bank capital helps maintain financial stability and reduces the financial distress of banks. However, various studies, such as those conducted (Islam & Nishiyama, 2016; Ozili, 2017; Saleh & Abu Afifa, 2020) have specifically found that profitability has a negative impact on credit risk. In contrast, a study of 44 Kenyan banks with data from 2000-2009 (Tarus, Chekol, & Mutwol, 2012) found that an increase in credit risk leads to increased profitability. In addition, using panel data from 2007-2015 in commercial banks in the United Kingdom, (Saeed & Zahid, 2016) found that credit risk has a positive impact on profitability. This study examined the impact of the global financial crisis of 2008 on the relationship between credit risk and profitability. This suggests that banks may charge increased fees, commissions, and interest rates to boost profitability while compensating for higher credit risk during economic downturns. Based on this perspective, we can derive a hypothesis for our study of Indonesian banks that profitability has an impact on credit risk.

Hypothesis 1: Profitability has a negative relationship with credit risk

Capital is a crucial factor in enhancing a bank's business operations and achieving superior performance. Capital availability enables banks to recapitalize and meet the needs of their customers more effectively and efficiently (Kargi, 2011; Menicucci & Paolucci, 2016). Utilizing available fund sources, such as liquid assets, for lending purposes can increase bank profitability, provided the risk-return relationship remains constant. However, empirical investigations of the relationship between capital and credit risk are relatively scarce, as most studies have primarily focused on the association between capital and bank profitability. Prior research by Islam and Nishiyama (2016); Ozili (2017) and Saleh and Abu Afifa (2020) demonstrated that capital has a negative relationship with profitability, where a decrease in profitability is often accompanied by a decrease in equity to absorb the losses from increased credit risk.

Based on the literature theory of capital by Diamond and Rajan (1999) an increase in credit risk can lead to an increase in bank capital if the borrower has moderate cash. This is because future promises from borrowers have a lower value under stricter capital requirements, and the threat of liquidation can increase the payments extracted. However, if the borrower has very little cash, the threat of liquidation can lead to bankruptcy. In addition, a study by Berger and DeYoung (1997) showed that banks that issue new shares tend to have higher capital ratios than those that do not, whereas a study by Flannery and Rangan (2006) showed that banks can increase their capital by retaining earnings and reducing dividend payments. Moreover, a recent study by Abbas and Ali (2022) in the field of Islamic banking showed that capital positively modifies the link between loan growth and credit risk. The study also showed that the effect of loan growth on credit risk varies by location and bank capitalization.

The relationship between bank capital and credit risk remains an area of substantial ambiguity. However, it is generally accepted that maintaining sufficient capital levels is crucial for banks to avoid excessive risks and ensure long-term financial stability. Therefore, the impact of bank capital on credit risk may depend on various factors, such as market conditions, regulatory requirements, and bank-specific characteristics. From this perspective, our study hypothesis for Indonesian banks is that bank capital has an impact on credit risk.

Hypothesis 2: Capital has a negative relationship with credit risk.

There are various measurements of credit risk, and in this study, we used the NPL ratio (NPL_R) as developed by Abbas et al. (2019); Kasinger et al. (2021); Minh Long, Thi Yen, and Dinh Long (2020); Phung et al. (2022); Pieter (2021) and Saleh and Abu Afifa (2020). As for the proxy for profitability, we used return on assets (ROA) (Abbas et al., 2019; Saleh & Abu Afifa, 2020) which demonstrated the use of ROA as a measurement of how effectively banks utilize their assets to generate returns. Finally, we used Abbas et al. (2019) and Jabbouri and Naili (2019)'s suggested ratio of total equity to total assets as a measure of capital.

3. METHODOLOGY AND DATA

This study used secondary data collection from the Indonesian finance service authority (OJK) website (https://www.ojk.go.id/en/Default.aspx) at "ELCTRONIC SERVICE" in submenu "Financial Report Publication" to obtain financial instrument variables for banks. For macroeconomic indicators, we obtained data on exchange rates and interest rates from the Indonesian Central Bank and data on economic growth from the Central Bureau of Statistics (htpps://bps.go.id).

The data used in this study were from January 2003 to September 2021, and they consisted of cross-sectional units of 117 banks and time series units of 225 monthly observations; 26,229 observations were available. In cases where data were missing in the middle of a time series, linear interpolation was used to fill them in. Each year, the (moving) average was used, and data cleansing was performed to maintain data integrity. As a result, 85 banks were selected as the research sample, with 117 months of observations, yielding 9,945 bank-year observations.

Banks can be classified into three ownership types: subsidiaries of foreign banks (Foreign), privately owned banks (Private), and state-owned banks (State). The macroeconomic variables examined in this study include gross domestic product (GDP) and the official benchmark government interest rate set by the Indonesian Central Bank, which indicates the prevailing interest rate. Previous studies employed benchmark interest rates and the GDP (Almaqtari, Al-Homaidi, Tabash, & Farhan, 2019; Naili & Lahrichi, 2022; Shawtari, 2018). However, only the GDP has been consistently used in research on bank performance (Abbas et al., 2019). These variables indicate external environmental factors that may affect bank performance. (Table 1 for an explanation of all the variables and our hypotheses).

Descriptive statistics, such as means and standard deviations, are commonly used at the beginning of quantitative data analysis to illustrate data trends and deviations (Table 2). Various empirical liquid reserve models in Chudik and Pesaran (Ditzen, 2018; Pesaran, 2007) in error correction model (ECM) format were computed using the DCCE econometric approach. This approach is preferred for large panels of data under the weak exogeneity assumption (Eberhardt & Teal, 2011). The model comprises two components: a long-run equation and a short-run equation. In empirical applications of economic models, particularly macroeconomic models, estimating long-run relationships is critical. Long-run relationships describe how one or more variables respond to changes in the steady state. The connections between macroeconomic variables like GDP and interest rates as well as exchange rates serve as examples of this.

Based on the hypotheses construction explained in the previous section, we construct the relationship between credit risk and the explanatory variables in the form of short-run (ECM) and long-run regression in the following equation:

$$Credit_{it} = \alpha_i + \beta 1_i Profit + \beta 2_i Capital + \beta Size + \beta FX_C + \beta Rate + \beta GDP + e \quad (1)$$

$$Credit_{it} = \alpha_i + \delta 1_i Profit + \delta 2_i Capital + \delta Size + \delta FX_C + \delta Rate + \delta GDP + \delta\ ECT\ t - 1 + \text{þ}\ e\ i;t$$

$$ECT_{t-1} = Cred\ t - 1 - \alpha 1 Profit\ it - 1 + \alpha 2 Capital\ it - 1 \quad (2)$$

Where: $Creditit$ is that Credit Risk (NPL_R), *Profit* is profitability (ROA), *FXc* is currency exchange code for the exchange rate between the United States dollar (USD) and the Indonesian rupiah (IDR), *Rate* is interest rate, and GDP is economic growth in Indonesia.

Equation 1 is the short-run equation, and Equation 2 is the long-run equation. Equation 1 and 2 are connected by the error-correction term (ECT); this is a lag-one-period long-run regression residual where the parameter δ measures the pace of adjustment. This parameter should be negative, with the absolute value strictly less than 1. A detailed description of variables, proxies, and their expected sign hypothesis (in relation to the dependent variable) is provided in Table 1.

Table 1. Variables, proxies and expected sign. The research hypotheses are given as expected impact sign against the dependent variable from the correlation matrix.

No	Variables	Proxy	Expected Sign
● Dependent variable			
1	Credit risk	Non-performing loan / Loan (NPL_R)	
● Independent variables			
2	Profitability	Operating income / Total assets (ROA)	Negative
3	Liquidity risk	Liquid asset / Total assets (LA_TA)	
4	Capital	Equity / Total assets (EQ_TA)	Negative
5	Error correction term		Negative
● Control variables			
6	Ownership	Ownership of entity (Type)	
7	Size	Log of bank assets (Size)	
8	Financial system stability	Exchange rate: USDIDR (FX_CH)	
		Interest rate (Rate)	
9	Structural factor	Gross domestic product (Growth)	
		COVID-19 period	

Since our data consist of a long panel (With the number of time series greater than the cross-section), it is important to pay special attention to certain points. These include the following: (a) non-stationarity (unit root), (b) cointegration, (c) slope heterogeneity, and (d) cross-sectional dependency.

In the econometric analysis, we assume that all variables in the model are non-stationary, meaning that they have a unit root process. To test for this hypothesis, we use two strict unit root tests: the Pesaran CADF (PESCADF) test for panel data with cross-section dependence (Pesaran, 2007) and the augmented Dickey Fuller-(ADF) test for time series data (Dickey & Fuller, 1979). The Pesaran CADF test is a more powerful test of unit roots than the traditional ADF test, as it takes into account cross-sectional dependencies among panel variables. The ADF test is a more robust variation of the test where structural breaks are present. By using these rigorous unit root tests to test for non-stationarity, we can ensure that our analysis is accurate and reliable.

For co-integration testing, we utilize a method that accounts for cross-section dependence. The method proposed by Persyn and Westerlund (2008) is employed, and rejection of the null hypothesis is taken as evidence of cointegration. In their study, Persyn and Westerlund (2008) generalized the design to encompass a wide range of possible dynamic structures. We used different criteria to check for cointegration, such as (a) the dependent variable (NPL_R); (b) the amount of lag used, which included leads and LR windows; (c) whether or not automated lag selection using the Akaike information criterion (AIC) was used; and (d) the use of bootstrap methods to get strong inference, as suggested by Blomquist and Westerlund (2014).

Data from long panels can present challenges because of the heterogeneity of the cross-section slope compared with the residual component (Eberhardt & Teal, 2011). To address this issue, we employ the method proposed by Pesaran and Yamagata (2008) and Blomquist and Westerlund (2013) to test for homogeneity of slopes against the assumption of heterogeneity. Our test specification includes the following: (a) alternative long-run specifications (NPL_R); (b) the use of standard errors of heteroscedasticity and consistent autocorrelation (HAC); and (c) the inclusion of descriptive variables such as cross-section mean and lag amount (0-3).

After conducting the slope heterogeneity test, we selected an appropriate version of the estimator. We used the mean group estimator in accordance with Pesaran and Smith (1995) recommendations if the test results showed slope heterogeneity. In contrast, Pesaran, Shin, and Smith (1999) reported that if we did not reject the assumption of slope homogeneity, we could use a pooled mean group estimator.

We conducted a robustness check to support the validity of our empirical findings. First, we evaluated the robustness of our results under different model settings by running an extension model with constant and trend parameters. Second, based on literature Atahau and Cronje (2022) we categorized the sample data into three groups based on bank ownership in Indonesia, including private banks (Private), foreign subsidiary banks (Foreign), and state-owned banks (State). This test was done to assess the robustness of our findings across various types of bank ownership. Finally, we conducted a regression analysis to examine how the COVID-19 pandemic affected credit risk, enabling us to assess the robustness of our findings over time and their sensitivity to the impact of a significant external shock.

4. EMPIRICAL RESULTS AND FINDINGS

4.1. Descriptive Statistics and Preliminary Analysis

The descriptive statistics for the variables used in this study are presented in Table 2. Based on the proximity of the mean and median and the lack of significant skewness, we can conclude that the variables are relatively well-behaved. In the banking industry, profitability is a crucial factor that affects a company's ability to obtain funding from creditors, attract investors to finance its operations, and expand its business. Effective governance in controlling credit risk and capital risk is essential for banks to make profits and satisfy shareholders, investors, creditors, and all other stakeholders. One of the primary variables used in this study is ROA, which is a frequently used indicator of corporate efficiency. The sample's median ROA is 0.026, and its average ROA is 0.045, indicating a positively skewed distribution of ROA values. This suggests that a small number of businesses with high ROA values may be driving the mean upward. Therefore, it is essential to carefully interpret the findings of this study and analyze the ROA data using the median as the central tendency measure.

Table 3 shows that none of the independent variables have a bivariate correlation that approaches 0.500. Based on our exploratory data analysis, we conclude that the data profile is not likely to have a significant impact on further studies.

Table 2. Descriptive statistics for the variables used in the study. The variables are in numeric values (Up to three decimals) except for Int rate (In percentage) and size (In million IDR). The descriptive statistics presented are the average, median, maximum, minimum, standard deviation and percentiles. The statistics are calculated for all the sample data.

Variable	Average	Median	Max.	Min.	St. dev.	Percentile		No. observations
						1%	99%	
NPL_R	0.029	0.025	0.121	0.000	0.023	0.000	0.121	9945
ROA	0.045	0.026	0.244	-0.099	0.057	-0.099	0.244	9945
LA_TA	0.262	0.251	0.556	0.062	0.099	0.062	0.556	9945
EQ_TA	0.210	0.177	0.781	0.094	0.122	0.094	0.781	9945
Size	7.259	7.213	9.037	5.753	0.683	5.753	9.037	9945
Int_rate	5.692	5.750	7.750	3.500	1.322	3.500	7.750	9945
growth	0.376	0.464	3.879	-3.025	1.071	-1.964	2.237	9945
FX_C	0.467	0.366	13.668	-9.049	2.582	-6.623	6.232	9945
Covid_19	0.179	0.000	1.000	0.000	0.384	0.000	1.000	9945

Table 3. Simpel bivariate correlation statistic (Pearson) between variables used in the study. Correlation statistics are calculated over the for all the sample data. Correlations are presented as a half triangle matrix.

Variable	NPL_R	ROA	LA_TA	EQ_TA	Size	Int_rate	Growth	FX_C	D_cov19
NPL_R	1.000								
ROA	-0.241	1.000							
LA_TA	-0.055	0.040	1.000						
EQ_TA	-0.023	-0.004	-0.007	1.000					
Size	0.008	0.132	-0.140	-0.015	1.000				
Int_rate	-0.166	0.085	0.040	-0.110	-0.123	1.000			
Growth	-0.021	-0.257	0.069	-0.014	-0.020	0.042	1.000		
FX_C	-0.027	0.037	0.017	-0.019	-0.024	0.082	0.108	1.000	
D_cov19	0.072	-0.102	0.162	0.046	0.078	-0.472	-0.029	-0.028	1.000

The unit root test results for the variables used in this study are shown in Table 4. These variables are NPL_R, ROA, LA_TA, EQ_TA, Size, Growth, INT_RATE, and FX_C. The unit root test was employed to assess the stationarity of a time series dataset, with the null hypothesis assuming non-stationarity of the dataset. The inference of unit root test findings within a panel data structure is notably more complex compared with its pure time-series counterpart (Pesaran, 2012). Existing panel data unit root tests posit the null hypothesis that all cross-section units are non-stationary, implying a homogenous test.

However, Pesaran (2012) research unveiled that rejecting the null hypothesis could indicate a non-zero fraction of non-stationary units. The current state of the literature suggests that the unit root test should be used to boost confidence in regression based on the assumption of cointegration. The results indicate that the variables NPL_R, ROA, LA_TA, EQ_TA, Size, and Growth significantly reject the non-stationary null hypothesis. Furthermore, this study applied PESCADF (Pesaran, 2007) and employed it (Im, Pesaran, & Shin, 2003; Levin, Lin, & Chu, 2002) yielding consistent results. This outcome is favorable as stationary time series are simpler to model and analyze, and the results obtained from them are more reliable. However, the variable INT_RATE exhibits significant non-stationarity, implying that it is a non-stationary time series.

Table 4. Unit root test result. Summary of some selected unit root tests performed on variables used in the study. This report covers (1) names of Variables, (2) names of corresponding unit root test methods used and (3) the conclusion of the test.

Variable	Method	Test statistics	P value	Result
NPL_R	PESCADF	-2,568	0.000	Reject heterogeneous non-stationary null hypothesis
ROA	PESCADF	-2,769	0.000	Reject heterogeneous non-stationary null hypothesis
LA_TA	PESCADF	-3,183	0.000	Reject heterogeneous non-stationary null hypothesis
EQ_TA	PESCADF	-3,080	0.000	Reject heterogeneous non-stationary null hypothesis
Size	PESCADF	-2,811	0.000	Reject heterogeneous non-stationary null hypothesis
Int_rate	ADF	0.103	0.9662	Cannot reject non-stationary null hypothesis
Growth	ADF	-5,341	0.000	Reject non-stationary null hypothesis
FX_C	ADF	-11,213	0.000	Reject non-stationary null hypothesis

Table 5 indicates that the null hypotheses of no cointegration cannot be rejected using subgroup or global criteria. However, upon further examination of the ECM model estimates, we can see that the ECT is highly significant. This suggests that there is an equilibrating mechanism, or cointegration, present in the data. We think that the lack of cointegration seen in Table 5 might be because of multicollinearity or endogeneity that we didn't notice in the risk proxies we used, namely capital and profitability. This could have caused what looked like a misalignment.

Table 5. Cointegration test. based on Persyn and Westerlund (2008) and Blomquist and Westerlund (2014) methods. Cointegration is based on various specifications, with NPL_R as the dependent variable. Null hypotheses are (1) global non-cointegration (Using Pt and Pa test statistics) and (2) subset cointegration (Using Gt and Ga) for all specifications.

No	Specification	Results (H0)	Statistic	Gt	Ga	Pt	Pa
1	NPL_R ROA LA_TA EQ_TA size , lags (2-3)	Cointegration	Z - value	-2.799	-4.503	-5.337	-7.561
	Leads (2-3) lrwindow; AIC(lag: 2.04 ; lead 2.06)		p - value	0.003	0.000	0.000	0.000
2	NPL_R ROA LA_TA EQ_TA size , constant	Cointegration	Z - value	-1.348	-4.227	-4.129	-6.874
	lags (2-3) leads (2-3) lrwindow AIC(lag: 2.04 ; lead 2.06)		p - value	0.089	0.000	0.000	0.000
3	NPL_R ROA LA_TA EQ_TA size , constant trend	Cointegration	Z - value	0.099	-3.235	-2.199	-4.658
	lags (2-3) leads (2-3) lrwindow AIC(lag: 2.04 ; lead 2.07)		p - value	0.539	0.001	0.014	0.000
4	NPL_R ROA LA_TA EQ_TA size , constant	Cointegration	Z - value	-2.211	-4.246	-5.337	-7.561
	lags (2) leads (2) lrwindow 1 , bootstrap		*Robust*	0.000	0.000	0.000	0.000
5	NPL_R ROA LA_TA EQ_TA size , constant	Cointegration	Z - value	-1.092	-2.641	-4.851	-6.572
	lags (3) leads (3) lrwindow 1 , bootstrap		*Robust*	0.000	0.000	0.000	0.000
6	NPL_R ROA LA_TA EQ_TA size , constant	Cointegration	Z - value	-1.092	-0.869	-4.974	-5.292
	lags (3) leads (3) lrwindow 2, bootstrap		*Robust*	0.000	0.000	0.000	0.000
7	NPL_R ROA LA_TA EQ_TA size , constant trend	Cointegration	Z - value	0.479	-3.164	-2.199	-4.658
	lags (2) leads (2) lrwindow 1 , bootstrap		*Robust*	1.000	1.000	0.000	00000
8	NPL_R ROA LA_TA EQ_TA size , constant trend	Cointegration	Z - value	2.281	-0.705	-1.424	-3.008
	lags (3) leads (3) lrwindow 1 , bootstrap		*Robust*	1.000	1.000	0.000	0.000
9	NPL_R ROA LA_TA EQ_TA size , constant trend	Cointegration	Z - value	2.281	1.775	-1.545	-1.184
	Lags (3) leads (3) lrwindow 2 , bootstrap		*Robust*	1.000	1.000	0.000	1.000

Finally, the slope homogeneity null hypothesis is convincingly rejected, as shown in Table 6. Therefore, the mean group type estimator should be used to estimate the regressions. Since the post-estimation procedure strongly suggests the presence of cross-sectional dependence, we do not report the ex-ante cross-sectional dependence test results. Therefore, to improve the estimation of the equation, cross-sectional averaging of the variables was necessary because of the presence of cross-sectional dependence. Our estimation method is now known as a dynamic common correlated effect error estimator with mean group variant (DCCE-MG) as a result of this work.

Table 6. Results of the slope heterogeneity test. Performed using the method proposed by Pesaran and Yamagata (2008) and Blomquist and Westerlund (2013). There are several specifications based on (1) whether NPL_R is a dependent variable, (2) inclusion of a cross-sectional average, and (3) heteroscedasticity treatment. Null hypotheses are slope homogeneity for all specifications.

No	Specification	Unadjusted delta		Adjusted delta	
		Delta	P - value	Delta	P – value
1	NPL_R ROA LA_TA EQ_TA size FX_C Int_rate GDP	17,679	0.000	18,494	0.000
2	NPL_R ROA LA_TA EQ_TA size FX_C Int_rate GDP, HAC	34,741	0.000	36,343	0.000
3	NPL_R ROA LA_TA EQ_TA size FX_C Int_rate GDP crosssection	20,573	0.000	21,557	0.000
4	NPL_R ROA LA_TA EQ_TA size FX_C Int_rate GDP cross-section, HAC	11,320	0.000	11,862	0.000

Table 7. Regression results using proposed specifications in a preliminary analysis. The estimated coefficient and standard error are presented.

Variables	Baseline regression
Dep Var = NPL_R	
Long-run equation	
ROA	-0.057* (0.034)
LA_TA	0.014* (0.008)
EQ_TA	0.035 (0.046)
Size	0.000 (0.023)
Short-run equation	
ECT	-0.436*** (0.021)
D.ROA	-0.011*** (0.004)
D.LA_TA	0.008*** (0.003)
D.EQ_TA	-0.041*** (0.011)
D.size	-0.029*** (0.008)
D.FX_C	0.000 (0.000)
D.growth	0.000 (0.000)
D.int_rate	0.002*** (0.001)
ECM specifications	
Cross section averages and constant	
Observations	9,860
R-squared	0.546
F stat	3.76***
CD test	91,94***
Number of groups	85

Note: Significance levels used denote as ***/* for p < 1%, and p < 10%, respectively.

4.2. Regression and Diagnostics

In our analysis, Table 7 reveals that NPL_R is significantly related to ROA, LA_TA, EQ_TA, Size, and Rate. However, our long-run and short-run models indicate that ROA has an adverse effect. Furthermore, in the long run equation. EQ_TA was found to be statistically insignificant. Our findings suggest that the effects of ROA and EQ_TA on credit risk (NPL_R) are more reactive than long-term adjustments. These results demonstrate a negative relationship between ROA and NPL_R, which confirms Hypothesis 1.

This finding aligns with our expectation that an increase in credit risk leads to greater difficulties for borrowers in loan repayment, thereby affecting financial profitability and potentially resulting in bank failure. These findings are consistent with prior research studies (Islam & Nishiyama, 2016; Ozili, 2017; Saleh & Abu Afifa, 2020) but they differ from those published by Saeed and Zahid (2016) and Tarus et al. (2012). This highlights the importance of considering both short-term and long-term variables in evaluating credit risk in banks.

According to the findings of this investigation on capital risk, there is a statistically insignificant association between EQ_TA and NPL_R, which contradicts Hypothesis 2. This conclusion suggests that banks may have already implemented measures to safeguard their capital during the analysis period, which includes the COVID-19 era, in anticipation of potentially deteriorating conditions induced by the pandemic. Acharya, Mehran, Schuermann, and Thakor (2012) and Maji and De (2015) have conducted research on the topic of capital preservation.

The regressions conducted in our study provide robust support for the ECM. We observed substantial evidence of an error-correction mechanism, indicating that adjustments to the dependent variable occur over time. Specifically, the MG estimate for the ECT is -0.436, suggesting a time lag of approximately 2.29 months (=1/0.436). Furthermore, upon reviewing the existing literature, we have not come across similar research that compares directly with our study, which highlights the novelty of our findings in this area. In addition, the CD test yields significant statistics, indicating that cross-sectional dependence occurs and is significant.

4.3. Robustness Test

In this study, we conducted three robustness tests. First, we ran an extension model with constant and trend parameters to test the robustness of our results under different model specifications (Table 8). Second, we split the sample data into the three following ownership categories of banks in Indonesia: private banks (PRIV), foreign subsidiary banks (FOR), and state-owned banks, including local government banks (SOE)-(Table 9). This enabled us to assess the robustness of our results across different types of bank ownership. Lastly, we conducted a regression analysis to examine the effect of the COVID-19 pandemic on credit risk (Table 10). This test allowed us to evaluate the robustness of our results under different time periods and to test the sensitivity of our findings to the impact of a major external shock. In Table 8, we present the results for the first robustness test conducted in our study, in which the estimated coefficient for the ECT plays a crucial role in the DCCE2 regression analysis. This coefficient represents the time lag in the equilibrium process, ranging from approximately 2.11 months (1/0.474) to 3.73 months (1/0.268), depending on the specific model employed. The difference in importance between the MG model and the DCCE model is because the DCCE model can take into account cross-sectional dependence in panel data. This means that it gives more accurate and consistent results that better reflect the features of panel data. In addition, the DCCE model may incorporate additional variables or interactions that are not accounted for in the MG model. Upon careful examination of the models and baseline regression, we found that the results of the baseline regression (models 1-3) were consistent with the non-cross-sectional approach. However, the inclusion of additional parameters such as the constant and trend introduced sensitivity to the results. In contrast, employing the cross-sectional approach (models 4-6) rendered more robust and statistically significant results, particularly with the inclusion of the constant and trend parameters.

Table 8. Robustness test with other variables. This table reports estimations of the baseline model with the dependent variable. The table presents the e stimated coefficients and standard error. Each regression model (denoted by a number in the first line of each column heading) corresponds to specific specifications inclusion of constant and application of cross-section average, by alternating proxies in the variables of interest (DCCE class estimators).

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dep Var = NPL_R	**(Base no cross)**	**(Base + Const)**	**(Base + Const+Tren)**	**(Base cross)**	**(Base cross cont)**	**(Completed)**
Long run equation						
ROA	-0.048***	-0.048***	-0.044***	-0.047**	-0.047**	-0.041*
	(0.017)	(0.017)	(0.014)	(0.022)	(0.022)	(0.024)
LA_TA	0.003	0.003	0.010	0.012	0.012	0.016**
	(0.009)	(0.009)	(0.007)	(0.008)	(0.008)	(0.007)
EQ_TA	0.002	0.002	-0.006	-0.014	-0.014	-0.006
	(0.030)	(0.030)	(0.019)	(0.020)	(0.020)	(0.017)
Size	0.026***	0.026***	-0.002	-0.021	-0.021	-0.021
	(0.006)	(0.006)	(0.016)	(0.014)	(0.014)	(0.014)
Short run equation						
ECT	-0.268***	-0.268***	-0.327***	-0.436***	-0.436***	-0.474***
	(0.017)	(0.017)	(0.019)	(0.021)	(0.021)	(0.022)
D.ROA	-0.003	-0.003	-0.005*	-0.011***	-0.011***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
D.LA_TA	0.015***	0.015***	0.012***	0.009***	0.009***	0.007***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
D.EQ_TA	-0.035***	-0.035***	-0.031***	-0.033***	-0.033***	-0.032***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
D. size	-0.047***	-0.047***	-0.039***	-0.024***	-0.024***	-0.022***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
D.FX_C	0.000***	0.000***	0.000***	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D. growth	-0.000***	-0.000***	-0.000***	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D. Int_rate	-0.002***	-0.002***	-0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Trend			0.000			0.000
			0.000			0.000
Constant		-0.149***	0.027		0.255***	0.206
		(0.046)	0.113		(0.078)	0.251
ECM specification						
Constant	N	Y	Y	N	Y	Y
Trend	N	N	Y	N	N	Y
Crosssection average	N	N	N	Y	Y	Y
Observations	9,860	9,860	9,860	9,860	9,860	9,860
R-squared	0.725	0.725	0.701	0.578	0.725	0.725
F stat.	3	3.01	3.10	3.31	3.8	3.8
CD test	257.01	257.01	252.16	90.29	90.29	90.29
Number of groups	85	85	85	85	85	85

Note: Significance levels used denote as ***/**/* for p-value p < 1%, p < 5%, p < 10%, respectively.

For further analysis, we selected Model 6 to compare the results across different bank ownership types in Table 9 and to evaluate the impact of the COVID-19 pandemic on credit risk in Table 10. We found that ROA and EQ_TA were negatively linked to NPL_R in Model 6. The estimated coefficients match the initial hypothetical signs shown in Table 1 (our first and second hypotheses). Moreover, in all models, the CD test yielded significant statistics, indicating the presence of cross-sectional dependence. For the second robustness test (Table 9) in this study, we conducted a dynamic regression analysis on the robustness test by dividing bank ownership into the three following parts: private owned banks (PRIVATE), foreign subsidiary banks in Indonesia (FOREIGN), and government-banks (STATE) (Atahau & Cronje, 2022).

The results of this analysis indicate that the coefficient for the equilibrium process had a time lag of between 1.93 months (1/0.517) and 2.20 months (1/0.453), depending on the ownership category of the banks being analyzed. The study found that the ECT estimates were qualitatively consistent with the robustness test results using NPL_R as a credit risk indicator. This shows that private banks are the most sensitive to changes in the economy as a whole. Specifically, the ECT estimates for private banks (PRIV) were -0.517 or 1.93 months, indicating a faster response to events that affect credit risk, such as news about rising interest rates in the central bank. This is in contrast to state-owned banks (SOE), which had an ECT estimate of -0.467 or 2.38 months.

According to the robustness test in Table 9, privately owned banks exhibit a consistent relationship with our first robustness test (model 6) in both the short- and long-run equations, providing robust evidence. However, there is a contrasting sign observed between foreign and state-owned banks. The situation with foreign banks in Indonesia is different; in the long-run equation, ROA has a positive correlation but is not significant with NPL_R, while EQ_TA is negatively significant with NPL_R. The reason for this result could be foreign banks penetrating the Indonesian financial system market and using a " cherry-picking " strategy by selectively lending to high-quality borrowers with less risky credit profiles; this strategy could be associated with funding a big project (Natsir, Soedarmono, Yudhi, Trinugroho, & Warokka, 2019).

In state-owned banks, we observe a contrasting relationship between ROA and NPL_R in the short term compared to the long term. Specifically, there is a positive correlation between ROA and NPL_R, as well as a significant negative correlation between EQ_TA and NPL_R in the short term. However, this relationship will reverse in the long term. This pattern can be attributed to the differing objectives and priorities of state-owned banks, which prioritize financing infrastructure projects rather than maximizing profits in the short term. In the long-run equations, we found a significant negative correlation between ROA and credit risk in state-owned (SOE) banks. This can be explained by the distinct borrower profile of state banks compared to private and foreign banks, as state banks primarily focus on providing financing for infrastructure projects. These findings align with previous studies conducted by Naili and Lahrichi (2022) and Atahau and Cronje (2022).

Table 9. Robustness check regressions using different samples of private/foreign/state owned banks. The estimated coefficient and standard error. The regression model corresponds to specification inclusion of constant and application of cross-section average (DCCE class estimators).

Variables	All banks	Private	Foreign	State
Dep var = NPL_R				
Long-run equation				
ROA	-0.041* (0.024)	-0.008 (0.035)	0.011 (0.046)	-0.101*** (0.031)
LA_TA	0.016** (0.007)	0.021* (0.011)	0.060*** (0.016)	0.013 (0.010)
EQ_TA	-0.006 (0.017)	-0.005 (0.029)	-0.180* (0.110)	0.025 (0.026)
Size	-0.021 (0.014)	-0.007 (0.020)	-0.160** (0.072)	-0.025 (0.019)
Short-run equation				
ECT	-0.474*** (0.022)	-0.517*** (0.031)	-0.453*** (0.063)	-0.467*** (0.035)

Variables	All banks	Private	Foreign	State
D.ROA	-0.011*** (0.003)	-0.015*** (0.005)	-0.014** (0.007)	0.000 (0.002)
D.LA_TA	0.007*** (0.002)	0.009** (0.004)	0.008 (0.006)	0.004 (0.004)
D.EQ_TA	-0.032*** (0.010)	-0.026 (0.016)	-0.000 (0.017)	-0.040*** (0.013)
D. size	-0.022*** (0.007)	-0.021** (0.011)	-0.015 (0.018)	-0.023*** (0.008)
D.FX_C	0.000 (0.000)	0.000* (0.000)	0.000 (0.000)	-0.000 (0.000)
D. growth	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
D. Int_rate	0.002*** (0.000)	0.001* (0.001)	-0.002** (0.001)	0.001*** (0.000)
Trend	0.000 0.000	0.000 0.000	0.000 0.000	0.000 0.000
Constant	0.206 0.251	0.34 0.205	0.19 0.436	0.472 0.261
ECM specification				
Constant	Y	Y	Y	Y
Trend	Y	Y	Y	Y
Observations	9,860	4,872	1,276	3,712
R-squared	0.725	0.572	0.472	0.386
F stat.	3.8	3.2	4.79	4.79
P-value	0	0	0	0
CD test	90.29***	25.53***	3.71***	57.01***
Number of groups	85	42	11	32

Note: Significance levels are used denoted as ***/**/* for $p < 1\%$, $p < 5\%$, and $p < 10\%$, respectively.

The third robustness test (Table 10) aimed to examine the impact of the COVID-19 pandemic on credit risk by dividing the sample data into different periods. Specifically, the year 2020 was chosen as the cutoff point to represent the onset of the pandemic in Indonesia. The decision-making processes for borrower determination have undergone changes because of the effects of COVID-19. To account for this, a dummy variable was introduced to indicate the COVID-19 period. The results of the robustness test in Table 10 demonstrate that the relationship observed in the period before COVID-19 remains consistent with our first robustness test (model 6) in both short- and long-run equations, providing robust evidence. However, during the COVID-19 period, the relationship exhibits a reversed sign.

Table 10. This table reports estimations of the baseline model with a dependent variable (NPL_R = Credit risk). The table presents the estimated coefficient and standard error. The regression model correspondents to specification inclusion of constant and application of cross section average (DCCE class estimators).

Variables	Baseline	Before COVID (<2020)	Covid period ('20-'21)
Dep var = NPL_R			
ROA	-0.041* (0.024)	-0.038*** (0.013)	1.309 -1.123
LA_TA	0.016** (0.007)	0.023** (0.009)	0.562 (0.609)
EQ_TA	-0.006 (0.017)	-0.010 (0.022)	-3.352* -1.854
Size	-0.021 (0.014)	0.004 (0.017)	-2.334 -1.639
Short run equation			
Ect	-0.474*** (0.022)	-0.430*** (0.024)	-0.657*** (0.073)
D.ROA	-0.011*** (0.003)	-0.000 (0.003)	-0.092** (0.039)
D.LA_TA	0.007*** (0.002)	0.011*** (0.004)	0.029* (0.016)

Variables	Baseline	Before COVID (<2020)	Covid period ('20-'21)
D.EQ_TA	-0.032*** (0.010)	-0.030** (0.014)	0.006 (0.046)
D.Size	-0.022*** (0.007)	-0.035*** (0.008)	-0.028 (0.040)
D.FX_C	0.000 (0.000)	0.000*** (0.000)	-0.000 (0.000)
D.growth	-0.000 (0.000)	-0.001*** (0.000)	-0.000 (0.000)
D.Int_Rate	0.002*** (0.000)	-0.002*** (0.000)	-0.001 (0.002)
D.Cov 19			-0.002 (0.002)
Trend	0.000 0.000	0.000 0.000	0.000 0.000
Constant	0.206 0.251	0.020 0.116	17.580 12.552
ECM specification			
Constant	Y	Y	Y
Trend	Y	Y	Y
Observations	9,86	8,075	1,785
R-squared	0.701	0.68	0.129
F stat.	3.1***	2.72***	2.68***
P value	0	0	0
CD test	254.20***	247.05***	6.64***
Number of groups	85	85	85

Note: Significance levels used denote as ***/**/* for p-value $p < 1\%$, $p < 5\%$, $p < 10\%$, respectively.

This suggests that banks adjusted their operational strategies in response to the pandemic. Specifically, we observed a positive relationship between ROA and credit risk and a negative association with EQ_TA. This indicates that banks have relied on internal sources of funding to increase risk and pursue higher fees and margins to achieve profitability. This finding contrasts with the results of our first test in Table 7 (Section 4.2), supporting the literature by Saeed and Zahid (2016) and Tarus et al. (2012) but contradicting the studies by Islam and Nishiyama (2016); Ozili (2017) and Saleh and Abu Afifa (2020). The results of the analysis indicated that there is a time lag between the coefficient for the equilibrium process and its impact on credit risk. Specifically, the analysis showed that the time lag ranges from 1.52 months (1/0.657) to 3.06 months (1/0.327). Contrasting with the use of NPL_R as a credit risk indicator during the COVID-19 period, the ECT estimate shows a quick response of 1.5 months (1/0.657). We did three more robustness tests and found that ROA and EQ_TA have a negative relationship with NPL_R. This match the signs we thought would happen in Section 2. This finding aligns with the literature by Islam and Nishiyama (2016); Ozili (2017) and Saleh and Abu Afifa (2020) which indicates a negative relationship between credit risk, specifically measured by NPL_R, and bank performance. Ultimately, this negative correlation with bank performance has implications for the capital position of banks.

5. CONCLUSIONS

Our study provides evidence that profitability and capital are key drivers of credit risk in Indonesian banks, but the relationship should be analyzed in conjunction with other risk factors. These findings have important implications for bank management, regulators, and investors aiming to achieve quality profit outcomes. In light of these findings, it may be necessary to develop, validate, and implement new risk indicators that are more relevant. To examine the empirical relationship between credit risk and selected variables such as profitability, liquidity risk, capital, and bank size, we employed the DCCE model in an ECM framework. Our analysis utilized a monthly panel dataset comprising 85 banks from January 2012 to September 2021, resulting in 9,945 bank-month observations. Highly significant ECT coefficients representing a time lag of 2.11 to 3.73 months ranged from 0.474 to 0.268, supporting the empirical design. The robustness of the ECT forecast was confirmed through various validation tests. Our results indicate a statistically significant negative relationship between ROA and EQ_TA and NPL_R, where ROA has a greater impact. This finding is consistent with our initial hypothesis and is in line with previous studies (Berger & Bouwman, 2013; Dietrich & Wanzenried, 2011; Islam & Nishiyama, 2016; Ozili, 2017; Saleh & Abu Afifa, 2020). To test the robustness of our findings, we conducted stress tests by isolating samples divided by ownership structure and period before and during the COVID-19 pandemic, and our study found robust samples divided by ownership structure to be reasonably robust when conducted before and during the COVID-19 pandemic, providing support for the reported results. However, previous stand-alone testing that found no cointegration should be considered. There may be undetected multicollinearity structures in risk proxies that call the results into question. Therefore, the alignment between the findings of the ECT estimate and the cointegration test may require a reassessment of the panel's cointegration test technique.

Our findings suggest that profitability and capital are the primary drivers of credit risk in Indonesian banks, but they must be viewed in conjunction with their risk implications. Future research might also analyze the particulars dealing with liquidity, as this study indicates that liquidity has important value. These results have important implications for bank managers, regulators, and investors. To ensure that banking operations are efficient and effective in minimizing risks connected with economic and macroeconomic situations and to achieve quality profits, novel and more impactful risk measures may need to be created, tested, and implemented.

Funding: This study received no specific financial support.
Institutional Review Board Statement: The Ethical Committee of the Bina Nusantara University, Indonesia has granted approval for this study on 26 June 2023 (Ref. No. 96000335676).
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: Upon a reasonable request, the supporting data of this study can be provided by the corresponding author.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Material preparation, data collection and analysis were performed, H.S., M., M.D.A; wrote the first draft of the manuscript, H.S. All authors have read and agreed to the published version of the manuscript.

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