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The Influence of Macroeconomic Factors on Credit Risk of Banks in Indonesia using ARDL Model

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ABSTRACT

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Autoregressive distributed lag; Commercial banks; Covid-19 Pandemic; Indonesian Government; Macroeconomic; NPL.

One of the efforts to maintain economic stability during the Covid-19 pandemic is to reduce the risk of in the banking sector. One of the risks in the banking sector that must be anticipated is credit risk. Non-Performing Loan (NPL) is one of the indicators used to detect credit risk. There are various factors that can affect credit risk, both from internal and external banking. One of the external factors that can affect NPL is macroeconomic conditions. This study aims to identify macroeconomic factors that affect banking NPLs in Indonesia using the autoregressive distributed lag (ARDL) model. The data used is time series data from January 2015 – August 2020, which period describes the condition of the Indonesian economy before and during the Covid-19 pandemic. The data consists of six variables, namely the NPL ratio of commercial banks and macroeconomic factors in Indonesia such as gross domestic product (GDP), inflation rate, USD-IDR exchange rate, benchmark interest rates [BI 7-Day (Reverse) Repo Rate], and credit growth. The results of the data analysis show that the NPL ratio and macroeconomic variables are experiencing shocks due to the COVID-19 pandemic. The results of the ARDL model analysis show that these macroeconomic variables are able to explain the NPL of 66.61%.

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1. Introduction

The Covid-19 pandemic that has occurred globally and has hit various countries in the world has prompted every country to make various policy strategies to deal with the crisis. Generally, the policies of each country prioritize the safety and health of its people, but do not rule out the economic conditions of the nation and state. Various steps have been taken by the Indonesian government to combat the Covid-19 pandemic, such as large-scale social restrictions (PSBB), campaigns for clean and healthy living habits, procurement and administration of vaccines, and the implementation of restrictions on community activities (PPKM). In addition, the Government of Indonesia is making full efforts to keep the economy running and stable during the Covid-19 pandemic.

One sector that is closely monitored by the government is the banking sector. The role of banks in encouraging activity and maintaining economic stability during the Covid-19 pandemic is very important, so it needs to be managed prudently. Some of the reasons for the importance of prudent bank management are first, the amount of public funds (third party funds) it manages is very large, where the amount can reach 90% of its total liabilities [1]; second, the role of banks as intermediary institutions reduces transaction costs and information asymmetry [2]. The placement of third-party funds in banks is generally in the short term, while the management of these funds is in the form of lending to the public in the long term. This encourages opaque business activities (loan quality cannot be observed and can be hidden for a long time) and is strictly regulated by regulators, which is another unique feature of banks [3].

One of the risks in the banking sector that must be anticipated is credit risk. Credit risk is an inseparable part of its core business, because the provision of credit is the core business and main source of bank income, so credit quality is the main indicator of financial performance and soundness [4]. Credit risk is also a trigger for systemic risk for banks, because failure in one bank will cause vulnerability to other banks. In addition, credit risk is also the most important aspect in understanding financial stability [5] and one of the crucial factors affecting banking stability [6], [7]. The most commonly used indicator as a proxy for credit risk is the ratio of non-performing loans (NPL) to total loans [8].

A number of empirical studies support this picture that failed banks have a high proportion of NPLs before going bankrupt and asset quality is a statistically significant predictor in determining insolvency. In 33 banking crises during 1977-2002, the NPL ratio ranged from 17% to 33%. Reinhart and Rogoff (2010) also conclude that NPL can be used as an early indicator of a crisis [9]. NPL is the root of the banking crisis and is a representation of credit risk at the aggregate level and a sign of failure in the banking system. In line with these researchers, Olivares-Caminal and Miglionico (2017) also conclude that a high NPL ratio has an impact on company stability and the financial system [10].

There are various factors that can affect credit risk, both from internal banking and from external banking. Internal factors that can affect NPL are financial conditions and banking-specific factors. Even though they have influence, internal factors cannot be the main factors that affect NPL. This is because most of the conditions of the community or credit takers are more influenced by external banking factors. External factors that can affect NPL such as macroeconomic conditions, disasters, and others. Independently, studies on the causal relationship between macroeconomic factors and NPL have been carried out by several researchers previously. Exclusively, each of these researchers uses different methods and case studies.

For case studies outside Indonesia, most of the previous studies used the panel data method to analyze the effect of macroeconomic factors on NPL [11], [12], [13], [14], [15], [16], [17]. From these studies, there are several studies that use generalized method of the moments (GMM) estimation [14], [16], [18]. On the other hand, there are several studies that use a simple statistical approach, namely multiple linear regression based on Ordinary Least Square (OLS) estimation [19], [20]. In contrast to other studies, Nikolaidou and Vogiazas used the autoregressive distributed lag (ARDL) method to model NPL [21], [22]. The results obtained from all these studies indicate that NPL can be explained by several macroeconomic variables.

For the case in Indonesia, Yusuf and Fakhruddin (2016) analyzed the effect of macroeconomic variables and financial ratios on NPL using multiple linear regression models [23]. Then, Ekananda (2017) discusses the cointegration technique of macroeconomic impact on NPL [24], where the model used is the vector error correction model (VECM) which was originally introduced by Engle and Granger (1987) [25]. The use of the ARDL method to model NPL was carried out by Sinay et al (2022). The modeling is to investigate the impact of bank-specific factors on NPL [26].

As a method of econometric analysis, autoregressive distributed lag (ARDL) provides information about the relationship between several variables based on time [27]. Therefore, cointegration is a powerful way to detect a steady state balance in an economic model that uses time series data [28]. Compared to other cointegration techniques, ARDL has several advantages, namely that all variables are assumed to be endogenous, different variables can have different amounts of lag and the technique can be used for small samples [29], [30], and It is not necessary to determine the degree of integration of variables because both zero degree $I(0)$ and first degree $I(1)$ can be used [29], [22].

Based on the description above, the use of the ARDL model in analyzing the relationship between macroeconomic factors and banking NPLs in Indonesia is still relatively new. Therefore, this study aims to identify macroeconomic factors that affect NPL in Indonesia using an autoregressive distributed lag (ARDL) model approach. This model is effective because the data used is time series data. This study is limited to the analysis of the ARDL model by Pesaran & Shin (1999) [31] and does not discuss the analysis of the ARDL Bound test [32].

2. Research Methods

The Autoregressive Distributed Lag (ARDL) model was developed by Pesaran and Shin in 1999 [31]. This model is denoted by ARDL $(p, q_1, \dots, q_k)$, where p is the number of lags in the dependent variable, q_1 is the number of lags of the first explanatory variable, and q_k is the number of lags of the k^{th} explanatory variable. The mathematical equation of the ARDL model is written as follows:

$$y_t = \alpha + \sum_{i=1}^{p} \gamma_i y_{t-1} + \sum_{j=1}^{k} \sum_{i=0}^{q_j} X_{j,t-i}{}' \beta_{j,i} + \varepsilon_t \quad (1)$$

Some explanatory variable, X_j, which has no lag ($q_j = 0$). These variables are called static regressors or fixed regressors. An explanatory variable that has at least one form of lag is called a dynamic regressor.

The data used in this study is time series data for the period January 2015 – August 2020, where from February 2020 to August 2020, Indonesia experienced an emergency condition due to the Covid-19 Pandemic. The data is monthly data sourced from Financial Services Authority (OJK) [33] and Bank Indonesia. The data consists of several variables as follows:

a. NPL ratio, which is a comparison of the number of non-performing loans (quality of Substandard, Doubtful and Loss). The variable is denoted by NPL.

b. Macroeconomic factors:
   - Economic growth is a change in the aggregate output or income of a country. The proxy used is gross domestic product (GDP). This variable is denoted by GDP.
   - The inflation rate is a general change in prices in a country's economy. The proxy used is the value of inflation. The variable is denoted by INF.
   - The interest rate is the benchmark interest rate issued by the central bank. The proxy used is the Bank Indonesia interest rate [BI 7-Day (Reverse) Repo Rate]. The variable is denoted by $BIrate$.
   - Exchange rate is the relative price of a country's currency against other countries' currencies. The proxy used is the rupiah exchange rate against the United States dollar (IDR/USD). The variable is denoted by the $Kurs$.
   - Credit growth is a change in aggregate lending by all commercial banks. The variable is denoted by $Loan$.

Based on equation 1, the empirical model will be developed as follows

$$NPL_t = \alpha + \sum_{i=1}^{p} \gamma_i NPL_{t-i} + \sum_{j=1}^{k} \sum_{i=0}^{q_j} Macroeconic\ Factors_{j,t-i}{}' \beta_{j,i} + \varepsilon_t \quad (2)$$

All variables (NPL and macroeconomic factors) depend on the results of unit root test using Augmented Dickey-Fuller (ADF). Thus, these variables can be data in the level condition or in the first difference.

3. Results And Discussion

3.1. Data Characteristics

In the period January 2015 – December 2019 data on the NPL ratio of Commercial Banks in Indonesia shows a seasonal pattern in which the NPL ratio increases every year **(Figure 1)**. This causes the NPL data to contain a trend. The increase in NPLs during this period indicated that Indonesia's economic condition was relatively stable and there was no rapid spike or increase **(Figure 1)**.

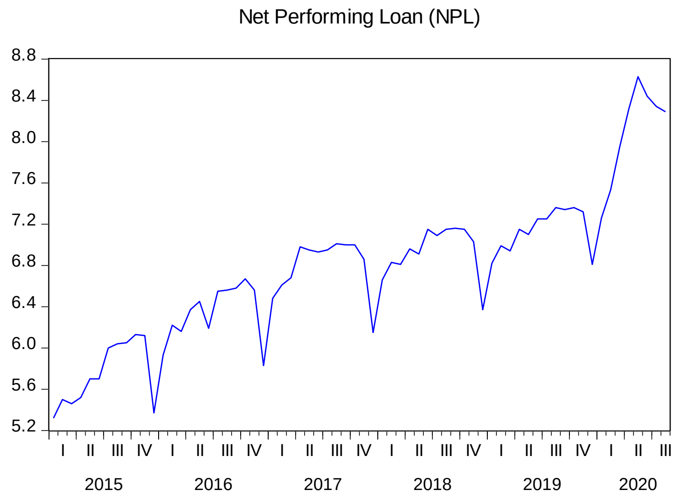

Figure 1. NPL Ratio of Banking in Indonesia 2015 – 2020

In contrast to the previous period, in 2020, the NPL ratio in Indonesia experienced a rapid spike or increase and the pattern was different from previous years. The increase started from the first quarter of 2020 to the second quarter of 2020 **(Figure 1)**, which peaked in May 2020, reaching 8.63% **(Table 1)**. This condition is one of the impacts of the COVID-19 pandemic that occurred in Indonesia. The NPL ratio was at its peak (turning point) in May 2020 and experienced a slow decline, until August 2020 the NPL ratio reached 8.29% **(Figure 1)**.

Table 1. Statistical description of the data

Variable	Mean	Standard Deviation	Minimum	Maximum
NPL	6.769118	0.736240	5.32	8.63
GNP	4.217794	2.550635	-5.32	5.27
INF	3.796029	1.488927	1.32	8.36
$BIrate$	5.529412	1.155397	4	7.75
$Kurs$	13851.76	667.2507	12625.00	16367.00
$Loan$	4723591.	658920.9	3667163	5781564.

Data source: Results from the EViews software

Apart from NPL, there are statistical descriptions of five macroeconomic variables, namely GDP, inflation, benchmark interest rate (BI rate), USD exchange rate, and credit growth which are shown in **Table 1**. GDP is an important indicator in assessing economic growth in Indonesia. Based on **Table 1**, the highest GDP occurred in the second quarter of 2018 which was 5.27%, while the lowest GDP occurred in the second quarter of 2020 which was -5.32%. This shows that GDP experienced a significant decline when COVID-19 hit Indonesia. Other macroeconomic variables are also experiencing the impact of COVID-19. In August 2020 the inflation rate in Indonesia decreased and reached 1.32% **(Table 1)**. This value is the lowest inflation rate in the last 6 years. During the COVID-19 pandemic, BI's policy in setting the benchmark interest rate was to lower the benchmark interest rate. In August 2020, BI set the benchmark interest rate at 4% **(Table 1)**. The interest rate is the lowest value in the last 6 years. This aims to maintain economic stability, especially for the banking sector and to suppress the inflation rate in Indonesia. In the last 6 years, the exchange rate of the United States Dollar (USD) against the Rupiah (IDR) experienced the highest increase in value during the COVID-19 Pandemic, namely in February 2020 of IDR. 16,367 **(Table 1)**. Credit growth conditions in Indonesia during the COVID-19 pandemic experienced an increase, where the highest value occurred in March 2020.

3.2. NPL Modeling Based on Macroeconomic Factors

Pre-processed data

The initial assumption that must be met by the ARDL model is that each variable must be integrated at degree 0 ($I(0)$), degree 1 ($I(1)$), or both, but not at degree 2 ($I(2)$). One way to detect the order of integration of each variable is through the unit root test. The test used is the Augmented Dickey-Fuller (ADF) test. The null hypothesis (H_0) is data containing unit roots, while the alternative hypothesis (H_1) is data that does not contain unit roots, namely stationary data. Thus, data classified as $I(0)$ is stationary data at the initial condition (level), while data classified as $I(1)$ is stationary data in the first difference process.

The results of the ADF test which are summarized in **Table 2** are the test results of each variable. These results state that the NPL, GDP, BI Rate, and Credit variables are $I(1)$, while the INF and Exchange Rate variables are $I(0)$. These results show that there are no variables included in $I(2)$. Thus, these variables meet the initial assumptions for ARDL modelling.

Table 2. ADF and Multicollinearity test

Variable	Level condition		First Difference		Integrated Degree	VIF
	ADF Test	p value	ADF Test	p value		
NPL	-1.506136	0.5245	-9.653029	0.0000	$I(1)$	-
GNP	-0.368398	0.9079	-8.109402	0.0000	$I(1)$	1.251818
INF	-2.947850	0.0453	-	-	$I(0)$	3.155204
$BIrate$	-1.354493	0.5992	-5.988613	0.0000	$I(1)$	2.515777
$Kurs$	-3.090476	0.0320	-	-	$I(0)$	2.676976
$Loan$	-1.139406	0.6951	-4.029043	0.0024	$I(1)$	3.772828

Data source: Results from the EViews software

One of the assumptions of the Ordinary Least Square (OLS) model is that there is no multicollinearity in the model. The ARDL model is an OLS-based model, so it is necessary to do a multicollinearity test on the independent variables. The indicator used is the Variance Inflation Factor (VIF) value. A model is said to be multicollinearity-free if the VIF value 10. **Table 2** shows the VIF values of each independent variable more than 10. Thus, multicollinearity does not occur.

NPL Model

Figure 2 shows the results of the lag model selection based on the Akaike Information Criteria (AIC) values. These results show that the $ARDL(6,5,6,1,3,6)$ model has the smallest AIC value of -0.463. Based on the results of the lag selection, the $ARDL(6,5,6,1,3,6)$ model is the model with the optimum lags.

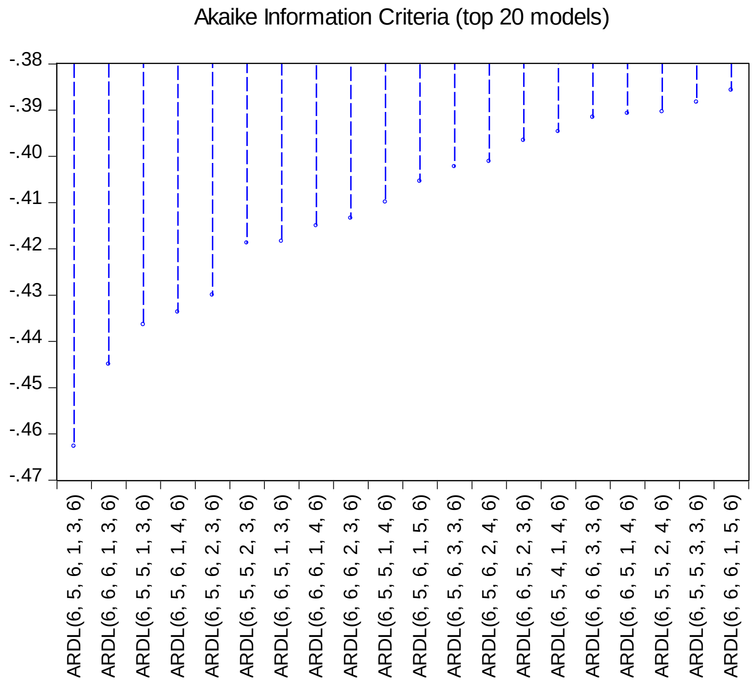

Figure 2. Lag selection based on the AIC

Based on **Equation (2)**, the mathematical equations of the $ARDL(6,5,6,1,3,6)$ are shown as follows.

$$\Delta NPL_t = C + \sum_{i=1}^{6} \gamma_i \Delta NPL_{t-i} + \sum_{i=0}^{5} \beta_{1,i} \Delta GNP_{t-i} + \sum_{i=0}^{6} \beta_{2,i} INF_{t-i} + \sum_{i=0}^{1} \beta_{3,i} \Delta BIrate_{t-i} + \sum_{i=0}^{3} \beta_{4,i} Kurs_{t-i} + \sum_{i=0}^{6} \beta_{5,i} Loan_{t-i} \tag{3}$$

The estimation results of γ dan β parameters and are presented in **Table 3**.

Table 3. Estimation Results of $ARDL(6,5,6,1,3,6)$

Variable	Coefficient (γ dan β)	Standard Error	t-Statistic	p value
ΔNPL_{t-1}	0.239704	0.157398	1.522918	0.1390
ΔNPL_{t-2}	0.017672	0.147935	0.119459	0.9058
ΔNPL_{t-3}	-0.063687	0.174015	-0.365985	0.7171
ΔNPL_{t-4}	-0.037003	0.176228	-0.209975	0.8352
ΔNPL_{t-5}	-0.471596	0.178366	-2.643977	0.0133*
ΔNPL_{t-6}	-0.576904	0.162202	-3.556699	0.0014*
ΔGNP	0.143668	0.045509	3.156917	0.0038*
ΔGDP_{t-1}	-0.032940	0.037041	-0.889296	0.3814
ΔGDP_{t-2}	-0.136560	0.089249	-1.530100	0.1372
ΔGDP_{t-3}	0.069455	0.049727	1.396725	0.1735
ΔGDP_{t-4}	-0.003748	0.045740	-0.081936	0.9353
ΔGDP_{t-5}	0.971423	0.333086	2.916435	0.0069*
INF	-0.061735	0.041456	-1.489177	0.1476
INF_{t-1}	0.000314	0.046094	0.006817	0.9946
INF_{t-2}	0.141771	0.050588	2.802498	0.0091*
INF_{t-3}	-0.208602	0.059675	-3.495623	0.0016*
INF_{t-4}	0.198813	0.065628	3.029375	0.0052*
INF_{t-5}	-0.144293	0.069671	-2.071066	0.0477*
INF_{t-6}	0.060405	0.046270	1.305479	0.2024
$\Delta BIrate_{t-1}$	-0.473668	0.179827	-2.634021	0.0136*
$Kurs$	0.000162	7.09×10^{-5}	2.283141	0.0302*
$Kurs_{t-1}$	4.57×10^{-5}	8.89×10^{-5}	0.514290	0.6111
$Kurs_{t-2}$	0.000211	0.000104	2.019326	0.0531
$Kurs_{t-3}$	-0.000328	9.82×10^{-5}	-3.346668	0.0023*
$\Delta Loan$	-5.28×10^{-6}	9.42×10^{-7}	-4.311235	0.0000*
$\Delta Loan_{t-1}$	-4.63×10^{-7}	1.14×10^{-6}	-0.403951	0.6893
$\Delta Loan_{t-2}$	-7.33×10^{-7}	1.20×10^{-6}	-0.610216	0.5466
$\Delta Loan_{t-3}$	6.77×10^{-7}	1.00×10^{-6}	0.675727	0.5048
$\Delta Loan_{t-4}$	9.80×10^{-7}	8.53×10^{-7}	1.148745	0.2604
$\Delta Loan_{t-5}$	-1.37×10^{-6}	8.48×10^{-7}	-1.609107	0.1188
$\Delta Loan_{t-6}$	-2.03×10^{-6}	9.95×10^{-7}	-2.044567	0.0504
C	-0.872752	0.886719	-0.984249	0.3334

R-squared = 0.844186; Adjusted R-squared = 0.666114; AIC = -0.463; Wald test: F-statistic = 0.0021, p value = 0.0000

*Significant for α = 5%
Data source: Results from the EViews software

Table 3 also shows the results of the parameter significance test either simultaneously or partially. The results of the simultaneous parameter significance test using the Wald test stated that the overall coefficient obtained was significant at the significance level of 5%. However, the results of the partial test, there are coefficients that are not significant at the significance level of 5%.

Test of Assumptions and Model Stability

The results of the residual assumption test of the $ARDL(6,5,6,1,3,6)$ obtained that the residuals are normally distributed because the p value of the JB test statistic is more than 5% **(Table 4)**. The model is also free from serial correlation (autocorrelation) based on the results of the LM test where the p value is more than 5% **(Table 4)**. Then, the results of the BPG test stated that the residual model was homoscedastic where the p value was more than =5% **(Table 4).** Thus, the $ARDL(6,5,6,1,3,6)$ model is a suitable (best) model because it fulfills all OLS assumptions.

Table 4. Residual Assumption Test

Assumption Test	Statistic value	p value
Jarque-Bera (JB) for Normality	0.4273	0.8076
Lagrange Multiplier (LM) for Autocorrelation	1.7716	0.4124
Breusch-Pagan-Godfrey (BPG) for Heteroscedasticity	28.3684	0.6510

Data source: Results from the EViews software

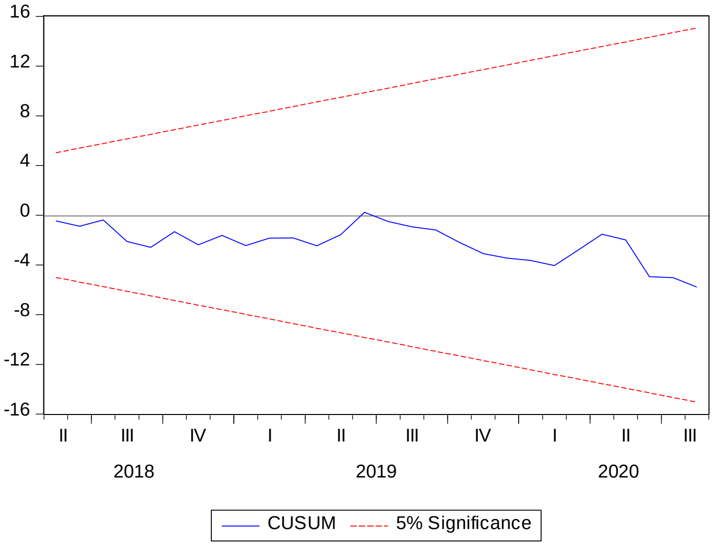

Figure 3. CUSUM Stability Test

Checking the stability of the model coefficients using the CUSUM test shown in **Figure 3**. The plot shows that the CUSUM values (blue solid line) are between the 5% significance limit (red dashed line). This means that $ARDL(6,5,6,1,3,6)$ is a stable model.

Model Interpretation

Based on the results of the partial parameter significance test, the NPL ratio was significantly affected at the significance level 5% by the NPL ratio variable at the 5^{th} lag and 6^{th} lag. This means that the NPL ratio in the previous 5 and 6 months affects today's NPL ratio. Then, at the significance level of 5%, the NPL ratio is significantly affected by the GDP variable and the GDP variable at the 5th lag. This means that changes in GDP at present and in the previous 5 months will affect the NPL ratio. For the inflation variable, the 2^{nd}, 3^{rd}, 4^{th}, and 5^{th} lag variables are variables that affect the NPL ratio at a significance level of = 5%. At the significance level = 5%, the BI 7-Day (Reverse) Repo Rate and the first variable lag have a significant effect on the NPL ratio. Likewise for the exchange rate variable and the third lag variable affect the NPL ratio at a significance level of 5%. Meanwhile, for the credit growth variable, only today's variable affects the NPL ratio at the confidence level = 5%. Based on the value of Adjusted R^2, the NPL ratio can be explained by the model obtained by 66.61%, while 33.39% is explained by other factors outside the model.

4. Conclusions

The data used is time series data from January 2015 – August 2020, which period describes the condition of the Indonesian economy before and during the Covid-19 pandemic**.** In the period February 2020 - August 2020, Indonesia's economic conditions experienced shocks due to the impact of the Covid-19 Pandemic. This can be shown by the value of GDP which fell to minus. Besides that, the variables such as NPL ratio, inflation, the benchmark interest rate [BI 7-Day (Reverse) Repo Rate], USD exchange rate and credit growth have also experienced the impact of COVID-19. This can be seen from the extreme changes in values that are not the same as in previous years.

The use of ARDL in modelling NPL is quite effective, because it can identify factors that have a direct impact on bank credit failures in Indonesia. Based on the analysis of the ARDL model, macroeconomic variables such as GDP, inflation rate, USD-IDR exchange rate, BI 7-Day (Reverse) Repo Rate, and credit growth were able to explain the NPL of 66.61%.

References

[1] J. R. Macey and M. O'Hara, "The Corporate Governance of Banks," *Economic Policy Review,* vol. 9, no. Special Issue, p. 91 – 108, 2003.

[2] B. Scholtens and D. van Wensveen, "The Theory of Financial Intermediation: An Essay On What It Does (Not) Explain," SUERF – The European Money and Finance Forum, Vienna, 2003.

[3] R. Levine, "Finance and Growth: Theory And Evidence," NATIONAL BUREAU OF ECONOMIC RESEARCH, Massachusetts, 2004.

[4] S. H. Boahene, J. Dasa and S. K. Agyei, "Credit risk and profitability of selected banks in Ghana," *Research Journal of Finance and Accounting,* vol. 3, no. 7, pp. 6-14, 2012.

[5] A. Ali and K. J. Daly, "Modelling Credit Risk: A comparison of Australia and the USA," *Journal of International Finance and Economics,* vol. 10, no. 1, pp. 123-131, 2010.

[6] G. Fainstein and I. Novikov, "The Comparative Analysis of Credit Risk Determinants in the Banking Sector of the Baltic States," *Review of Economics & Finance,* vol. 1, no. June, pp. 20-45, 2011.

[7] R. Mileris, "Macroeconomic Determinants of Loan Portfolio Credit Risk in Banks," *Engineering Economics,* vol. 23, no. 5, pp. 496-504, 2012.

[8] K. I. Nikolopoulos and A. I. Tsalas, "Non-performing Loans: A Review of the Literature and the International Experience," in *Non-Performing Loans and Resolving Private Sector Insolvency: Experiences from the EU Periphery and the Case of Greece*, Palgrave Macmillan Cham, 2017, pp. 47-68.

[9] C. M. Reinhart and K. S. Rogoff, "Growth in a Time of Debt.," *American Economic Review,* vol. 100, no. 2, pp. 573-578, 2010.

[10] R. Olivares-Caminal and A. Miglionico, "Non-performing Loans: Challenges and Options for Banks and Corporations," in *Non-Performing Loans and Resolving Private Sector Insolvency: Experiences from the EU Periphery and the Case of Greece*, Palgrave Macmillan , 2017, pp. 17-45.

[11] A. Glogowski, "Macroeconomic Determinants of Polish Banks' Loan Losses – Results of a Panel Data Study," Department of Information and Public Relations - National Bank of Poland, Warsaw, 2008.

[12] M. Nkusu, "Nonperforming loans and macro financial vulnerabilities in advanced economies," International Monetary Fund, 2011.

[13] D. P. Louzis, A. T. Vouldis and V. L. Metaxas, "Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios," *Journal of Banking & Finance,* vol. 36, no. 4, pp. 1012-1027, 2012.

[14] P. Jakubík and T. Reininger, "Determinants of Nonperforming Loans in Central, Eastern and Southeastern Europe," *Focus on European Economic Integration,* vol. 2013, no. 3, pp. 48-66, 2013.

[15] N. Klein, "Non-Performing Loans in CESEE: Determinants and Impact on Macroeconomic Performance," International Monetary Fund, 2013.

[16] A. Ghosh, "Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states," *Journal of Financial Stability,* vol. 20, no. C, p. 93–104, 2015.

[17] B. Skarica, "Determinants of non-performing loans in Central and Eastern European countries," *Financial Theory and Practice,* vol. 38, no. 1, pp. 37-59, 2014.

[18] V. Makri, A. Tsagkanos and A. Bellas, "Determinants of Non-Performing Loans: The Case of Eurozone," *Panoeconomicus,* vol. 61, no. 2, pp. 193-206, 2014.

[19] I. Bucur and S. E. Dragomirescu, "The Influence of Macroeconomic Conditions on Credit Risk: Case of Romanian Banking System," *Studies and Scientific Researches,* vol. Economics Edition, no. 19, pp. 84-95, 2014.

[20] T. Mondal, "Sensitivity of Non-Performing Loan to Macroeconomic Variables: Empirical Evidence from Banking Industry of Bangladesh," *Global Journal of Management and Business Research: C Finance,* vol. 16, no. 4, pp. 21-28, 2016.

[21] E. Nikolaidou and S. Vogiazas, "Credit Risk Determinants for the Bulgarian Banking System," *International Advances in Economic Research,* vol. 20, no. 1, pp. 87-102, 2014.

[22] E. Nikolaidou and S. Vogiazas, "Credit risk determinants in Sub-Saharan banking systems: Evidence from five countries and lessons learnt from Central East and South East European countries," *Review of Development Finance,* vol. 7, no. 1, pp. 52-63, 2017.

[23] M. R. Yusuf and Fakhruddin, "Analisis Variabel Makro dan Rasio Keuangan terhadap Kredit Bermasalah," *Jurnal Ilmiah Mahasiswa Ekonomi Pembangunan,* vol. 1, no. 2, pp. 555-562, 2016.

[24] Ekananda and Mahjus, "Analysis of the Macroeconomic Impact towards the NPL National Banking in Indonesia: The Study of Macro-Economic Shock Using Vector Autoregression Models," *European Research Studies Journal,* vol. XX, no. 3A, pp. 396-416, 2017.

[25] R. F. Engle and C. W. J. Granger, "Co-Integration and Error Correction: Representation, Estimation, and Testing," *Econometrica,* vol. 55, no. 2, pp. 251-276, 1987.

[26] L. J. Sinay, S. J. Latupeirissa, S. M. Pelu and M. I. Tilukay, "The Impact of Bank-Specific Factors on Non-Performing Loan in Indonesia: Evidence From ARDL Model Approach," *BAREKENG: Jurnal Ilmu Matematika dan Terapan,* vol. 16, no. 2, pp. 675-686, 2022.

[27] S. D. Vogiazas, "Determinants Of Credit Risk In The Bulgarian And The Romanian Banking Systems And The Role Of The Greek Crisis," Thesis submitted to the Department of Economics of Sheffield University in fulfillment of the requirements for the degree of Doctor of Philosophy, South East European Research Centre at Thessaloniki, 2015.

[28] E. Nkoro and A. K. Uko, "Autoregressive Distributed Lag (ARDL) Cointegration Technique: Application and Interpretation," *Journal of Statistical and Econometric Methods,* vol. 5, no. 4, pp. 63-91, 2016.

[29] N. Adeleye, E. Osabuohien, E. Bowale, O. Matthew and E. Oduntan, "Financial reforms and credit growth in Nigeria: Empirical insights from ARDL and ECM techniques.," *International Review of Applied Economics,* vol. 32, no. 6, pp. 807-820, 2018.

[30] G. Baoko, I. A. Acheampong and M. Ibrahim, "Determinants of bank credit in Ghana: a bounds-testing cointegration approach," *African Review of Economics and Finance,* vol. 9, no. 1, pp. 33-61, 2017.

[31] M. H. Pesaran and Y. Shin, "An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis," in *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium*, Cambridge University Press, 1999, pp. 371 - 413.

[32] M. H. Pesaran, Y. Shin and R. Smith, "Bounds Testing Approaches to the Analysis of Level Relationships," *Journal of Applied Econometrics,* vol. 16, no. 3, p. 289–326, 2001.

[33] Financial Services Authority (OJK), Indonesia Banking Statistics, Jakarta: Banking Licensing and Information Department, Financial Services Authority, Republic of Indonesia, 2021.