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Resilience Rural Banks Pasca Covid-19

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ABSTRACT

Beginning with a health crisis, the Covid-19 pandemic has had a domino effect on social, economic, and financial aspects. The economy has experienced a slowdown, accompanied by a decline in purchasing power due to reduced income. Tourist areas have become completely deserted, resulting in a lack of income and economic activity. The impact of the pandemic has inevitably spread to the banking sector, particularly affecting Rural Banks (known as BPR). The role of BPR, as part of the government's strategy for local economic development and labor absorption, has also been disrupted. In Indonesia, BPR has long been the backbone of microfinance, serving micro, small, and medium enterprises (MSMEs). However, the Covid-19 pandemic has shaken this sector, forcing BPRs to confront challenges while exploring new opportunities for resilience. This research recommends that Rural Banks strengthen risk management and operational efficiency to enhance their resilience in the future.This research contributes to the existing literature by providing a focused analysis of Rural Banks specific financial performance variables and recommends that Rural Banks strengthen risk management and operational efficiency to enhance their resilience in the future. The research employs logit analysis to develop a prediction model. The findings indicate that the resilience model can serve as a predictive tool for BPR resilience in the post-pandemic period, supporting economic empowerment, particularly for MSMEs and labor absorption. This study introduces the concept of Off-Balance Sheet management as a strategic tool for enhancing resilience, which has been underexplored in the context of rural banking in Indonesia.

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1. Introduction

The impact of the Covid-19 pandemic on MSME actors has resulted in a sales decline exceeding 50%, adversely affecting business profits by up to 90%. Additionally, cash availability has been limited to a maximum of three months, necessitating adjustments in employee needs. Business actors are compelled to economize on operational costs. Many borrowers from banks or financial institutions are experiencing payment difficulties. Increased volatility in financial markets and rising non-performing loans (NPLs) have negatively impacted the performance of the financial sector, placing the stability of the financial system on alert (Endri et al., 2020).

The empowerment and development of MSMEs are closely linked to the strategic role of BPRs (Puspitasari, 2021). BPR is one of the government's strategies for national economic recovery post-pandemic and labor absorption. BPR is expected to significantly contribute to serving MSMEs, particularly in financing businesses, increasing capital, and developing ongoing MSMEs to promote local economic resilience and labor absorption. The empowerment and development of MSMEs are closely linked to the strategic role of BPRs. From 2008 to 2018, 90 BPRs were subject to liquidation by the Deposit Insurance Corporation (LPS). In 2015, there were 1,800 BPRs, but by November 2021, only 1,631 BPRs were registered and operational, as illustrated in Graph 1.

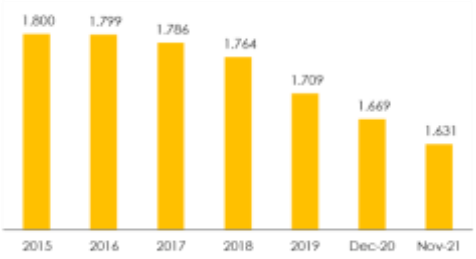

Fig. 1. Number of BPR/BPRS from 2015 to 2021

The Covid-19 pandemic presents a new challenge for BPR. Business activities in BPR have slowed, facing obstacles in managing operational costs, which has impacted BPR profitability. Therefore, a study on the resilience of BPR in the post-Covid-19 pandemic era is necessary. The research problem is how BPR can sustain itself in the post-Covid-19 pandemic period.

This study aims to analyze the resilience of BPR in the post-Covid-19 pandemic era through financial performance analysis to predict the risk of bank bankruptcy early by formulating an effective and accurate BPR resilience model to survive in the post-pandemic period with its accompanying impacts.

While numerous studies have been conducted on indicators of failure in the general banking sector, research on BPR resilience remains limited. BPR operates by collecting public funds in the form of savings and deposits and redistributing them to the community. BPR prioritizes channeling funds to the public in the form of credit, particularly to MSMEs. Thus, BPR is recognized as a type of bank providing banking services to MSME groups.

Studies on BPR in Indonesia have found that CAR, LDR, NPL, efficiency, and ROA are not indicators of bankruptcy in BPR (Yuliantini et al., 2019). Some studies using a logit approach in Indonesia have found that LDR, ROA, credit growth, and CAR significantly influence the bankruptcy risk of BPR (Pratiwi et al., 2019). Previous studies have indicated that off-balance-sheet (OBS) items affect bank health, as OBS can make financial statements appear more favorable, posing risks as management may use them for window dressing (Indrajati et al., 2020).

Further research has explored the determinants of financial distress in BPR leading to bank bankruptcy, indicating that solvency, profitability, and productivity are key factors in financial difficulties for BPR (Puspitasari, 2021). Testing the determinants of BPR resilience based on a composite index comprising CAR, cash ratio, and off-balance-sheet items was conducted in 2020. The results indicated that CAR is the most accurate determinant in predicting BPR bankruptcy, highlighting the need for banks to focus on capital adequacy (Napitupulu and Puspitasari, 2023).

The declining number of BPRs emphasizes the need for BPRs to refine their business management strategies, including those related to credit growth (PK) in fulfilling their intermediary functions and business efficiency. BPRs must avoid non-performing loans (NPLs) and optimize efficiency (BOPO) while paying attention to OBS transactions to enhance BPR performance. As a primary support source for MSMEs, BPRs need to implement prudential principles and adhere to sound banking practices to remain competitive in the banking industry (Puspitasari, 2021). Previous research has developed techniques for modeling bankruptcy risk in the banking industry, particularly for BPR. However, a gap remains in research investigating BPR resilience, especially in the post-Covid-19 pandemic context, particularly in developing countries like Indonesia.

Previous studies indicate a research gap. The model in this study is a variant of previous research to assess BPR resilience from the perspective of bankruptcy risk trends. This paper addresses the research gap by identifying these factors. The objective of this research is to model bank failure across all sizes. Therefore, this study employs proxy variables based on specific bank data from call reports. These variables, detailed in Table 1, are derived from previous literature on bank bankruptcy.

Table 1 Operational Variable

Variable Dependendent	
DEFAULT	Dummy Variable: equals one for unresilience banks, zero otherwise.
Variable Independent	
CAR	Equity capital/book value of total assets.
ROA	The bank's ability to generate profit from its assets.
LDR	The bank's ability to meet short-term obligations by dividing total loans by deposits.
PK	Growth of total loans disbursed to third parties.

The dependent variable DFAULT is a dummy variable for default. The four regressors in this model are inspired by variables used by Altman. This model aims to assess a bank's condition using financial data. CAR, which is the ratio of risk-weighted assets (credit, investments, securities, receivables from other banks) financed by the bank's own capital, serves as a proxy for capital adequacy (CAR). This variable indicates that the proxy variable is an indicator of the bank's actual condition (Kyriazopoulos, 2014). The next three early warning system variables serve as proxies for asset quality and portfolio risk. A high CAR positively impacts the amount of credit disbursed as long as third-party funds are sufficient, ultimately increasing bank income (Chieng, 2013). Credit growth (PK) serves as a proxy for productivity. PK represents the growth of total loans disbursed to third parties and significantly contributes to bank bankruptcy (Engida et al., 2015). This finding aligns with previous research concluding that PK is a significant factor (Jan dan Marimuthu, 2015). LDR is included as a proxy for liquidity risk. Banks are required to maintain liquidity to meet short-term obligations (Hogan, 2015).

2. Method

The data used in this study are secondary data, specifically monthly financial reports from Rural Banks (BPR) under the Jakarta Regional Office during the period 2021-2023. The sampling technique employed in this research is purposive sampling, based on specific characteristics or criteria of the population (Sugiyono, 2017). The sampling criteria used in this study are BPRs under the Jakarta Regional Office that published complete financial reports during the period from 2021 to 2023, totaling 203 banks. The first hypothesis test compares resilience banks with unresilience banks. The testing uses logistic regression to investigate whether the financial ratios in this study can predict the resilience condition of the banks.

The analysis method employs a logistic regression model. The dependent variable in this study is a dummy variable; where category 0 represents the resilience bank group and category 1 represents the unresilience bank group, using Altman's bankruptcy prediction tool. The independent variables used are financial ratios including liquidity, profitability, productivity, and solvency. This study also employs descriptive analysis to illustrate the relationships between the variables by examining mean values, standard deviations, maximum, and minimum values. In using multiple regression models, hypothesis testing must avoid potential deviations from classical assumptions deemed important to prevent issues in multiple regression analysis (Hair, 2012).

The logistic regression formulation is as follows:

$$\text{Ln}\ \frac{P}{(1-P)} = \beta 0 + \beta 1\text{CAR} + \beta 2\text{ROA} + \beta 3\text{CR} + \beta 4\text{PK} + \varepsilon \quad \ldots\ldots\ldots\ldots\ (1)$$

3. Results and Discussion

Table 1 shows the differences in financial ratios between unresilience and resilience banks.

Table 1. Descriptive Analysis

	Y	N	Mean	Std. Deviation	Z
CAR	Unresilience	381	29.710	21.859	-14.986***
	Resilience	837	37.844	22.262	
ROA	Unresilience	381	0.488	6.689	-33.380***
	Resilience	837	6.101	4.460	
LDR	Unresilience	381	83.702	13.916	-3.009***
	Resilience	837	81.977	13.259	
PK	Unresilience	381	5.890	0.440	-6.717***
	Resilience	837	6.007	0.487	

To determine whether the regression model is a good fit, it is necessary to conduct a feasibility test of the logistic regression model. This analysis is based on the Omnibus Tests of Model Coefficients. If the probability value > 0.05, the regression model is not feasible. If the probability value < 0.05, the regression model is feasible. The results of the model feasibility test can be seen in Table 2.

Table 2. Omnibus Tests of Model Coefficients

		-2 Log likelihood	Chi-square	df	Sig.
Step 1	Block 0	83.813	2309.54	9	.000
	Block 1	43.515	2309.54	9	.000

The independent variables, represented by financial ratios, can statistically predict the condition of banks experiencing financial distress or unresilience's BPRs, as indicated by a probability value of 0.000, which is less than 0.05, confirming the feasibility of the logistic regression model. Overall, this model demonstrates better analytical performance. This is evidenced by a decrease in the -2 log likelihood from 83.813 in block 0 to 43.515 in block 1, or a decrease in Chi Square of 2309.54. Thus, it can be concluded that the logistic regression model is feasible for use overall.

Table 3. Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	9.206	9	.323

To determine whether there is a difference between predictions and observations, a Hosmer-Lemeshow test is conducted using the Chi-square approach. The results of the test in Table 3 show the similarity of the logistic regression model predictions with the observed data, with a Chi-square value of 9.206 and a significance level of 0.323. With a significance value greater than 0.05, there is no significant difference between the logistic regression model predictions and the observed data. This indicates that the model can predict its observation values, or it can be said that the model is accepted because it aligns with the observation results. This means that the constructed model is fit to serve as a predictive model for bank resilience, particularly for BPR.

To clarify the prediction of the logistic regression model with the observation data, a classification table can be presented, which is a cross-tabulation between the logistic regression model predictions and the observed results. This cross-tabulation confirms the absence of significant differences between the logistic regression model predictions and the observed data. The results of this cross-tabulation model can be seen in Table 4.

Table 4. Classification Table

Observed			Predicted		
			Financial Distress		Percentage Correct
			Unresilience	Resilience	
Step 1	Bank	Unresilience	179	774	18.8
		Resilience	116	22903	99.5
Overall Percentage					96.3

a. The cut value is .500

The overall classification result for logistic regression is quite good, at 96.3%. The accuracy percentage for companies predicted to be unsustainable is 99.3%, with 179 observations predicted correctly and 774 observations predicted otherwise. The logit regression test was conducted on the independent variables at a significance level of 5% and 10%. The complete results of the logit regression test are presented in the following table:

After the text edit has been completed, the paper is ready for the template. Duplicate the template file by using the Save As command, and use the naming convention prescribed by your conference for the name of your paper. In this newly created file, highlight all of the contents and import your prepared text file. You are now ready to style your paper; use the scroll down window on the left of the MS Word Formatting toolbar.

Table 5. Variables in the Equation

Variable	Model
	Coefficient
CAR	-0.0095***
LDR	0.0346***
ROA	-0.2139***
PK	-0.6001***
C	-1.3050**
% Correct	96.45%
% Incorrect	3.55%

*) Significant at the 1 percent level.
**) Significant at the 5 percent level.
***) Significant at the 10 percent level.

Based on Table 1, the relationship between independent variables and the dependent variable is evident. The regression coefficient (beta) for the CAR variable is -0.0095 with significance at the 1 percent level. This indicates that the solvency ratio influences bank resilience. For the LDR variable, the regression coefficient (beta) is 0.0346 with significance at the 1 percent level, indicating that the liquidity ratio influences bank resilience. The return on assets variable has a regression coefficient (beta) of -0.2139 with significance at the 1 percent level, indicating that the profitability ratio influences bank resilience. Lastly, for the credit growth variable, the regression coefficient (beta) is -0.6001 with significance at the 1 percent level, indicating that productivity influences bank resilience. The regression equation can be expressed as follows:

$$Y = -1.3050 - 0.0095\mathbf{CAR} + 0.0346\mathbf{LDR} - 0.2139\mathbf{ROA} - 0.6001\mathbf{CG} + e$$

4. Conclusion

The independent variables, represented by financial ratios, can statistically predict the condition of banks experiencing financial distress, as indicated by a probability value of 0.000, which is less than 0.05, confirming the feasibility of the logistic regression model. Thus, BPRs can fulfill their role in meeting the needs and development of small and micro enterprises, as well as low- to middle-income communities, particularly in obtaining loan funds. Ensuring capital adequacy, implementing risk management, and adhering to sound banking governance principles are expected to yield high returns for BPRs, ultimately impacting the resilience of the bank and its role as infrastructure supporting the economic resilience of a region. The savings-investment gap will affect the resilience of economic growth in a region, particularly in improving the quality of life for communities and micro, small, and medium enterprises. Future research can be enriched by incorporating other variables not examined in this study and employing different methodologies.

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