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ARIMA-Based Analysis of Financial Risks in Islamic and Conventional Rural Banks

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Abstract

Purpose: This study aims to analyze and compare the financial risks of Islamic Rural Banks (BPRS) and Conventional Rural Banks (BPR) in Indonesia, focusing on liquidity and credit risks. The objective is to provide a comprehensive understanding of risk management patterns and performance differences between these two types of banks.

Methodology/approach: This study aims to analyze and compare the financial risks of Islamic Rural Banks (BPRS) and Conventional Rural Banks (BPR) in Indonesia, focusing on liquidity and credit risks. The data analysis used is time series analysis with the ARIMA method.

Results/findings: The findings reveal that BPRS generally maintains higher liquidity ratios with lower liquidity risk compared to BPR, although both bank types exhibit credit risk above the recommended threshold. The forecasting results indicate that BPRS is likely to maintain its liquidity and reduce non-performing financing in the coming period, while BPR faces declining liquidity and persistent non-performing loan issues.

Conclusion: Islamic and conventional rural banks show different financial risk profiles, with conventional banks facing higher liquidity and loan risks, while Islamic banks generally maintain stronger liquidity but remain exposed to financing risks.

Limitations: This study is limited by its focus on quantitative indicators and historical data, without incorporating qualitative or macroeconomic factors. The use of ARIMA may not fully capture sudden structural changes or regulatory impacts.

Contribution: The study offers insights for improving risk management and compares Islamic and conventional rural banks in a developing country.

Keywords: *ARIMA Forecasting, Conventional Rural Banks (BPR), Credit Risk, Islamic Rural Banks (BPRS), Liquidity Risk*

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1. Introduction

Islamic and conventional financial institutions have experienced asset growth and enhanced stability, enabling them to sustain strong performance (Le, Ho, Nguyen, & Ngo, 2022). At the micro level, these institutions have also demonstrated notable outcomes, accompanied by an increase in social capital (Chmelíková, Krauss, & Dvouletý, 2019). The broadening access to financial services for small businesses is expected to further encourage banks to expand their assets and capital bases. According to A. Khan, Rizvi, Ali, and Haroon (2021), both Islamic and conventional players particularly banks offer similar products, although they are based on different underlying principles.

Islamic institutions are recognized for their satisfactory performance and operational efficiency (A. Khan et al., 2021). However, the COVID-19 pandemic has affected the stability and profitability of the global financial industry. Both Islamic and conventional banks experienced a decline in revenue worldwide, although the former displayed slightly stronger resilience than their conventional counterparts (Le et al., 2022). The pandemic also increased operating expenses and slowed credit disbursement (Gong, Jiang, & Lu, 2021; Li, Feng, Zhao, & Carter, 2021). Small-scale banks were particularly vulnerable, as evidenced by deteriorating asset quality, heightened credit risk, and greater funding constraints, which collectively threatened their operational stability and long-term sustainability (Blasco, Corredor, & Satrústegui, 2023; Davydov, Vähämaa, & Yasar, 2021; M. F. Khan, Ali, Hossain, & Bairagi, 2023).

From a risk perspective, Islamic institutions are also not immune to shocks triggered by the pandemic-induced crisis (Rizwan, Ahmad, & Ashraf, 2022). One of the most common risks is credit risk, particularly for organizations with large-scale assets and substantial capital reserves. Entities with stronger repayment capacity tend to expand their market reach (Ajija, Sukmana, Sari, & Hudaifah, 2020). This expansion may lead to greater fund disbursement, which, in turn, elevates exposure to non-performing loans (NPLs). Consequently, the rate of return risk is also strongly influenced by borrower characteristics (Fianto, Maulida, & Laila, 2019). Furthermore, the pandemic caused several institutions to experience capital shortages and increased debt burdens Duan, El Ghoul, Guedhami, Li, and Li (2021), which inevitably affected their overall risk profile.

Liquidity risk remains a critical challenge for financial institutions, emerging from unexpected funding demands and large withdrawals (Ball, 2023). Effective liquidity management is essential to mitigate these risks (Alaoui Mdaghri (2022), yet holding excess reserves often reduces profitability (Chen, Chen, & Huang, 2021). Moreover, greater funding liquidity may lead banks to take higher risks, underscoring the importance of prudent liquidity strategies for financial stability (Abbas, Ali, Yousaf, & Wong, 2021). In this context, a comparison between Islamic and conventional microfinance institutions is relevant, as both face distinct trade-offs in balancing financial performance and risk. Islamic microfinance institutions tend to achieve broader outreach, while conventional ones show stronger financial results (Ahmad, Lensink, & Mueller, 2020). Evidence also indicates that income diversification benefits Islamic microfinance, whereas geographic diversification can hinder conventional institutions, with loan defaults generally being higher in Islamic systems under certain conditions (Ben Salem & Ben Abdelkader, 2023; Disli & Jalaly, 2024).

Extending this discussion, in Indonesia, Islamic Rural Banks (BPRS) and Rural Banks (BPR) have been compared, particularly during the Covid-19 pandemic. The findings suggest that BPRS is slightly more efficient, although BPR performs better in terms of capital, asset quality, profitability, and liquidity during the crisis (Hasbi, Apriyana, & Pangestu, 2021; Raharjo, Prasetyo, & Kristina, 2021). Further studies indicate that BPRS excels in profitability and efficiency, while BPR are stronger in risk management and liquidity (Santosa & Pribadi, 2021). Overall, comprehensive evaluations are crucial for improving the competitiveness and resilience of both banking models in the national economy.

Considering the conditions outlined above, it is crucial to analyze institutional risk levels using a time-series approach. This method enables the prediction of risk trends over time based on historical data. Several researchers, including Arumningtyas, Prahutama, and Kartikasari (2021), Sukono, Simanjuntak, Santoso, Ghazali, and Bon (2019), Rizkya, Syahputri, Sari, Siregar, and Utaminingrum (2019), Gunawan and Astika (2022), and Challa, Malepati, and Kolusu (2018), have employed the Autoregressive Integrated Moving Average (ARIMA) model to forecast risks, particularly within the banking sector.

Despite extensive research on the performance and resilience of Islamic and conventional financial institutions, existing studies remain predominantly cross-sectional and do not sufficiently capture the temporal dynamics of risk. This study seeks to fill this gap by employing the Autoregressive Integrated Moving Average (ARIMA) model to forecast risk levels and systematically compare institutional vulnerabilities and resilience. The results are expected to enrich the literature on financial risk management while providing robust empirical insights to guide policymakers in strengthening the systemic stability.

2. Literature Review

Duan et al. (2021), in their study on systemic bank risk during the COVID-19 pandemic, employed systemic risk variables using capital deficiency as a proxy variable. In addition, banks utilize non-performing loan (NPL) variables and the debt-to-equity ratio (DER) as proxies for risk. Similarly, X.Li et al. (2021), in their research on the impact of diversification on bank risk during the COVID-19 pandemic, measured risk variables by calculating the standard deviation of return on assets (RoA) and return on equity (RoE). Saif-Alyousfi and Saha (2021) also use the standard deviation of RoA, RoE, and loan loss reserves as proxies for bank risk. Meanwhile, Rizwan et al. (2022), in their study on the systemic risk of Islamic banks during the pandemic, used the Value at Risk (VaR) metric to assess systemic risk. Additionally, Bikker and Vervliet (2018), Widarjono, Anto, and Fakhrunnas (2020), and Chikalipah (2018) employed non-performing loans as a proxy to explain bank risk variables.

Ibrahim and Rizvi (2018) examined how Islamic and regular banks handle money, obtain deposits, and take on risk. Their research shows that Islamic banks are better at distributing funds than traditional banks and have lower risk levels. Bilgin, Danisman, Demir, and Tarazi (2021) also stated that conventional banks are more likely to fail during a financial crisis or when the economy is unstable at home than Islamic banks. Hidayat, Sakti, and Al-Balushi (2021) found no significant difference in risk levels between Islamic and conventional banks, which is contrary to the findings of this study. During the COVID-19 pandemic, the stock prices of Islamic financial institutions were less affected by the shocks caused by the pandemic than those of traditional financial institutions (Akkas & Al Samman, 2022). Also, the size of a bank is negatively correlated with risk, which means that banks with more assets are better able to protect themselves from financial risk (Farnè & Vouldis, 2021; Hidayah, Muslim, & Azis, 2022; Sumiansi, Fadjar, Sutomo, & Wanti, 2025).

Arumningtyas et al. (2021) employed the Autoregressive Integrated Moving Average (ARIMA) model to analyze and assess the risk level of bank stock returns. Similarly, Sukono et al. (2019) used the ARIMA model to evaluate the short-term risk of Indonesian firm stocks. Rizkya et al. (2019) applied the ARIMA approach to analyze time series data and forecast the demand for industrial products. Gunawan and Astika (2022) used the ARIMA model to predict fluctuations in the Composite Stock Price Index (CSPI) on the Indonesia Stock Exchange due to the COVID-19 pandemic. Challa et al. (2018) forecasted the stock beta values on the Bombay Stock Exchange, projecting stock risk and return levels using ten years of historical data. Additionally, Hidayana, Subiyanto, and Supian (2022) conducted a literature review comparing GARCH and ARIMA models for risk prediction and concluded that ARIMA outperforms in identifying extreme risk levels.

The reviewed literature highlights diverse approaches to measuring and forecasting bank risk, each with distinct strengths and limitations. Studies such as Duan et al. (2021), Li et al. (2021), and Saif-Alyousfi and Saha (2021)provide valuable insights by employing widely used accounting-based proxies like NPLs, DER, RoA, and RoE, yet these indicators tend to capture risk only in static or backward-looking terms. In contrast, Rizwan et al. (2022) advanced the discussion by applying Value at Risk (VaR), which offers a more market-oriented assessment of systemic risk, although it remains sensitive to model assumptions. Comparative studies by Ibrahim and Rizvi (2018), Bilgin et al. (2021), and Akkas and Al Samman (2022) highlight the relative resilience of Islamic banks, particularly during crises, but their conclusions are sometimes inconsistent with findings such as Hidayat et al. (2021), who reported no significant differences between bank types.

Moreover, research employing time-series forecasting methods, including Arumningtyas et al. (2021), Sukono et al. (2019), and Gunawan and Astika (2022), demonstrates the capacity of ARIMA to model dynamic risk patterns, providing a forward-looking perspective that is absent in static measures. However, these studies often focus narrowly on stock indices or firm-level data rather than systematically comparing Islamic and conventional banks' performance. Finally, Hidayana et al. (2022)

strengthen the case for ARIMA by showing its superiority over GARCH in identifying extreme risk levels, although broader validation across banking systems remains limited.

This study differs from prior studies that relied on static proxies such as NPLs, RoA, or VaR by employing the ARIMA model to capture the dynamic evolution of risk over time. This study differs from previous research by employing the ARIMA model not for stock indices or macroeconomic indicators but specifically for analyzing the financial statements of BPR and BPRS, as reported in the official Islamic Banking Statistics of Indonesia. Covering a relatively long period from 2012 to 2023, the dataset allows for a more robust and comprehensive time-series analysis of institutional risk than prior studies with shorter observation windows.

Furthermore, instead of relying solely on general accounting measures such as RoA or RoE, this study integrates more targeted financial ratios Loan-to-Deposit Ratio as a proxy for financing, non-performing financing for credit risk, and current assets to liabilities for liquidity thus providing a more precise and context-specific assessment of risk dynamics in Islamic and conventional rural banks. Drawing upon the previous literature and the analytical framework of this study, the following hypotheses are developed to investigate the comparative risk behavior of BPR and BPRS:

H1: There is a significant difference in financing, credit, and liquidity risks between BPR (Rural Banks) and BPRS (Islamic Rural Banks).

H2: The ARIMA model can effectively forecast the temporal evolution of financing, credit, and liquidity risks in BPR and BPRS.

3. Methodology

We employed the Autoregressive Integrated Moving Average (ARIMA) model for quantitative and time series analyses. The data were obtained from the financial statements of BPR (Rural Banks) and BPRS (Islamic Rural Banks), as published in the *Islamic Banking Statistics* available on the official website of the Financial Services Authority of the Republic of Indonesia, covering the period from 2012 to 2023. We used several financial ratios as proxies for the key variables in the model.

1. The Loan-to-Deposit Ratio (LDR), defined as the ratio of financing to total third-party funds, was used as a proxy for the financing ratio.
2. The credit risk variable is proxied by the ratio of non-performing financing to total financing.
3. The liquidity variable is measured as the ratio of current assets to total current liabilities.

The model equation is as follows:

$$\Delta Y=\phi_1 Y_{t-1}+\theta_1 \varepsilon_{t-1}+\varepsilon_t$$

Where:

$\Delta Yt=Y_t - Y_{t-1}$ (first differencing).

$\phi 1$ and $\theta 1$ are the coefficients that must be estimated from the data.

The analytical procedure of the ARIMA method in time series modeling generally encompasses three interrelated stages: stationarity testing, model estimation, and forecasting. The first stage, stationarity testing, is essential to ensure that the underlying series possesses a constant mean and variance over time, as non-stationary data may lead to spurious results and unreliable model performance. Statistical tests such as the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests are commonly employed to identify the presence of unit roots, while differencing transformations are applied when stationarity is not achieved.

Upon confirming stationarity, the next stage involves ARIMA model estimation, which requires the specification of autoregressive (p), differencing (d), and moving average (q) parameters. This process is typically guided by the analysis of autocorrelation and partial autocorrelation functions (ACF and PACF) and further validated using model selection criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Once the optimal model is identified, the final stage consists of forecasting, in which the fitted ARIMA model is used to generate future values of the time series.

4. Results and Discussion

4.1. Research Results Data

Table 1. Financial Ratio Data for Conventional Rural Banks

	Liquidity	**NPL**	**LDR**
Max	0,013	0,087	0,867
Min	0,004	0,044	0,726
Average	0,009	0,065	0,788
St Dev	0,001	0,011	0,032

Source: Researcher-processed data, 2024

Table 1 shows that BPRs recorded a maximum liquidity ratio of 13%, with an average of 1.3% and a median of 0.9%. These figures indicate that the overall liquidity level of BPRs is relatively low, suggesting a heightened risk of defaults. The proportion of liquid assets to total current liabilities reaches a maximum of only 13%, highlighting limited short-term financial flexibility for these firms. In terms of credit risk, the highest recorded non-performing loan (NPL) ratio among BPRs is 8.7%, with an average of 6.5%, which exceeds the regulatory threshold of 5% for NPLs as a share of total outstanding credit.

This suggests that credit disbursement practices among BPRs are suboptimal and expose institutions to elevated risk. Moreover, the credit-to-deposit ratio of BPRs is also relatively modest, implying that a significant portion of third-party funds collected is not channeled into lending activities. Based on these findings, we can infer that BPRs have yet to fully utilize their funding capacity for productive credit distribution.

Table 2. Financial Ratio Data for Islamic Rural Banks

	Liquidity	**NPF**	**FDR**
Max	0,936	0,118	1,357
Min	0,366	0,059	1,034
Average	0,874	0,086	1,187
St Dev	0,047	0,015	0,076

Source: Researcher-processed data, 2024

Table 2 shows that the BPRS recorded a maximum liquidity ratio of 93%, with an average of 87%. These figures suggest that the BPRS maintains a high level of liquidity, indicating a low risk of default. The ownership of liquid assets is more than sufficient to cover short-term liabilities, reflecting a strong short-term financial resilience. However, the highest recorded non-performing financing (NPF) ratio for BPRS reached 11.8%, with an average of 8.6%, which significantly exceeds the regulatory threshold of 5% for non-performing financing relative to the total credit disbursed. This indicates that the quality of financing disbursement is suboptimal and associated with a high level of credit risk for the bank.

The financing-to-third-party fund ratio of BPRS is very high, even exceeding the maximum regulatory threshold. This suggests that BPRS fully utilizes the funds collected from customers for financing activities. Such a high ratio also indicates that BPRS's revenue is heavily reliant on its ability to generate returns from financing operations, making its profitability closely tied to the performance of its financing portfolios.

4.2. Statistical Test Stages

Table 3. Stationarity Test of FDR Variable for BPRS

Null Hypothesis: D(FDR,2) has a unit root			
Exogenous: Constant			
Lag Length: 10 (Automatic - based on SIC, maxlag=12)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-18.23335	0.0000
Test critical values:	1% level	-3.486064	
	5% level	-2.885863	
	10% level	-2.579818	
***MacKinnon (1996) one-sided p-values.**			

Source: Researcher-processed data, 2024

The first step in this study was to conduct a unit root test to determine the stationarity of the time series data, thereby avoiding regression fallacy or spurious regression. Testing for stationarity is a crucial preliminary step in time-series analysis, as non-stationary data can lead to invalid statistical inferences. Because the data used in this study were time series in nature, a stationarity transformation was necessary. For variables found to be non-stationary at the level, the first differencing was applied to achieve stationarity.

In this study, the Augmented Dickey-Fuller (ADF) test was employed to examine stationarity using a 5% significance level (0.05). The unit root test was conducted from the level form to the second difference. The test at the second difference level was necessary because at both the level and first difference, none of the variables exhibited stationarity. The results at the second difference level confirmed that all variables became stationary, with p-values below the 0.05 significance level.

Table 4. Stationarity Test of Liquidity Variable for BPRS

Null Hypothesis: D(Liquidity,2) has a unit root			
Exogenous: Constant			
Lag Length: 11 (Automatic - based on SIC, maxlag=12)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-19.88681	0.0000
Test critical values:	1% level	-3.486551	
	5% level	-2.886074	
	10% level	-2.579931	
***MacKinnon (1996) one-sided p-values.**			

Source: Researcher-processed data, 2024

The unit root test was conducted up to the second-difference level. This was necessary because the test at the first difference still indicated that all variables were non-stationary. The results at the second difference level confirmed that all variables became stationary, with p-values below the 0.05 significance level. Accordingly, all variables in this study are integrated of order two, or I(2), which means that two levels of differencing are required to eliminate the non-stationary characteristics of the data. This condition suggests that the underlying time series exhibits a strong long-term trend that cannot be corrected by a single differencing process.

Table 5. Stationarity Test of NPF Variable for BPRS

Null Hypothesis: D(NPF,2) has a unit root			
Exogenous: Constant			
Lag Length: 10 (Automatic - based on SIC, maxlag=12)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-10.91472	0.0000
Test critical values:	1% level	-3.486064	
	5% level	-2.885863	
	10% level	-2.579818	
***MacKinnon (1996) one-sided p-values.**			

Source: Researcher-processed data, 2024

The unit root test was conducted up to the second difference level, as the results at the first difference indicated that all variables remained nonstationary. Consequently, the test at the second difference showed that all variables became stationary, with p-values below the 0.05 significance level. Based on these results, all variables in this study are classified as integrated of order two (I(2)), meaning that two rounds of differencing are required to achieve the stationarity. This finding suggests that fluctuations in each variable exhibit a strong long-term trend that cannot be eliminated through a single differencing process.

Table 6. Stationarity Test of LDR Variable for BPR

Null Hypothesis: D(LDR) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=12)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-11.34934	0.0000
Test critical values:	1% level	-3.481217	
	5% level	-2.883753	
	10% level	-2.578694	
***MacKinnon (1996) one-sided p-values.**			

Source: Researcher-processed data, 2024

Based on the results of the stationarity test using the unit root method, it was found that at the level form, the p-values were greater than the 5% significance level, indicating that the null hypothesis, which states that the data has a unit root or is non-stationary, cannot be rejected. This implies that the original data are still affected by long-term trends or persistent fluctuations, causing the mean and variance to be non-constant over time, and therefore violating the assumption of stationarity. However, after applying the first differencing transformation, the p-values fell below the 5% significance threshold, allowing us to reject the null hypothesis. This indicates that the data became stationary after transformation.

Table 7. Stationarity Test of Liquidity Variable for BPR

Null Hypothesis: D(Liquidity) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=12)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-16.57355	0.0000
Test critical values:	1% level	-3.481217	
	5% level	-2.883753	
	10% level	-2.578694	
***MacKinnon (1996) one-sided p-values.**			

Source: Researcher-processed data, 2024

This unit root test was conducted at the level of the first difference. The unit root test at the first difference was performed because the unit root test at the level showed that all variable values were nonstationary. Therefore, the results of the unit root test at the first difference indicate that all variable data became stationary with a probability below the 0.05 significance level. Thus, all variables in this study are integrated at order one or I(1), which means that only one differentiation process is needed to eliminate the non-stationary nature of the data. This condition indicates that the data have a long-term trend or pattern that can be addressed through first-order differencing, making the mean and variance constant over time. This finding serves as an important foundation for the next stage of the analysis, as the uniformity of the integration level among variables is a prerequisite for the cointegration test, which aims to identify the presence of a long-term relationship between these variables.

Table 8. Stationarity Test of NPL Variable for BPR

Null Hypothesis: D(NPL,2) has a unit root			
Exogenous: Constant			
Lag Length: 10 (Automatic - based on SIC, maxlag=12)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-15.30724	0.0000
Test critical values:	1% level	-3.486064	
	5% level	-2.885863	
	10% level	-2.579818	
***MacKinnon (1996) one-sided p-values.**			

Source: Researcher-processed data, 2024

The unit root test was conducted up to the second difference level, as the test at the first difference indicated that all variables remained nonstationary. However, at the second difference, the results showed that all variables became stationary, with p-values below the 0.05 significance level. Accordingly, all variables in this study are classified as integrated of order two (I(2)), which means that two rounds of differencing are required to eliminate their non-stationary properties. This result suggests that the variables exhibit persistent long-term trends, such that any changes or shocks to the system require a longer adjustment period before returning to equilibrium.

4.3. Estimation Test

Table 9. Estimation Results of the Financing-to-Deposit Ratio (FDR) Variable for BPRS

D.FDR	Coef	Std. Err	Z	P>| Z |	95% Conf	Interval
Const	.0015634	.0004898	3.19	0.001	.0006034	.0025233
ARMA						
AR						
L1	.863045	.0611836	14.11	0.000	.7431274	.9829627
MA						
L1	-1.000004	188.4547	-0.01	0.996	-370.3645	368.3645
/Sigma	.0226857	2.137706	0.01	0.496	0	4.212512

Source: Researcher-processed data, 2024

The estimation results presented in Table 9 indicate that the constant term (intercept) has a positive and statistically significant coefficient of 0.0015634 ($p = 0.001$), suggesting that, holding other variables constant, the dependent variable increases by approximately 0.00156 units, on average. The autoregressive component AR(1) exhibits a high positive coefficient of 0.863045 ($p < 0.000$) with a narrow confidence interval (0.7431274 to 0.9829627), implying strong persistence in the series and a substantial degree of dependence on its previous value. Conversely, the moving average parameter MA(1) is estimated at -1.000004 with a large standard error (188.4547) and is statistically insignificant ($p = 0.996$), indicating that it does not contribute meaningfully to explaining the variation in the dependent variable. The sigma parameter, representing the standard deviation of the residuals, was estimated at 0.0226857 and was not statistically significant ($p = 0.496$), suggesting no strong evidence of residual variance instability. Overall, the results highlight the dominance of the AR(1) process in explaining the dynamics of the dependent variable, while the MA(1) component and residual variance appear to have negligible effects on the dependent variable.

Table 10. Estimation Results of the Liquidity Variable for BPRS

Liquidity	Coef	Std. Err	Z	P>| Z |	95% Conf	Interval
Const	.8736093	.0134509	64.95	0.000	.8472461	.8999725
ARMA						
AR						
L1	-1.89918	.7705994	-2.46	0.014	-3.409527	-.3888327
L2	-.9199711	.7311663	-1.26	0.208	-2.353031	.5130885
MA						
L1	1.909001	.7888957	2.42	0.016	.3627941	3.455208
L2	.92259919	.7419421	1.25	0.212	-.528188	2.380172
/Sigma	.0465271	.001533	30.35	0.000	.0435225	.0495317

Source: Researcher-processed data, 2024

Based on the estimation results presented in Table 10, the constant term exhibits a positive and statistically significant coefficient (0.8736, $p < 0.000$), indicating a stable baseline level of liquidity in the model. The autoregressive component at lag 1 (AR L1) is negative and significant (-1.8992, $p = 0.014$), suggesting a strong inverse relationship between current liquidity and its first lag, implying mean-reverting dynamics. Conversely, the autoregressive term at lag 2 (AR L2) is negative but statistically insignificant (-0.9200, $p = 0.208$), indicating that its influence on liquidity fluctuations is negligible in the short run.

On the moving average side, the first lag (MA L1) displays a positive and significant coefficient (1.9090, $p = 0.016$), signifying that past shocks have a substantial and direct effect on present liquidity levels, whereas the second lag (MA L2) shows a positive but insignificant effect (0.9226, $p = 0.212$). The estimated standard deviation of the residuals (/Sigma) is relatively low (0.0465, $p < 0.000$), suggesting that the model captures most of the variation in liquidity with minimal, unexplained volatility. Collectively, these findings imply that short-term liquidity movements are heavily influenced by recent past values and shocks, with stronger effects observed in the first lag than in the second.

Table 11. Estimation Results of the Non-Performance Financing (NPF) Variable for BPRS

D.NPF	Coef	Std. Err	Z	P>| Z |	95% Conf	Interval
Const	-.0000319	.0003556	-0.09	0.928	-.0007289	.0006651
ARMA						
AR						
L1	.6319287	.3369802	1.88	0.061	-.0285404	1.292398
MA						
L1	-.7439631	.3174404	-2.34	0.019	-1.366135	-.1217913
/Sigma	.0048638	.000232	20.97	0.000	.0044092	.0053184

Source: Researcher-processed data, 2024

Based on the estimation results, the constant term for the differenced non-performing financing (D.NPF) is negative but statistically insignificant (-0.0000319, $p = 0.928$), indicating the absence of a meaningful intercept effect. The autoregressive term at lag 1 (AR L1) has a positive coefficient (0.6319) and is marginally insignificant at the 5% level ($p = 0.061$), suggesting that past changes in NPF may exert a moderate but not statistically conclusive positive influence on current changes in NPF. In contrast, the moving average component at lag 1 (MA L1) is negative and statistically significant (-0.7440, $p = 0.019$), implying that previous NPF shocks have a corrective effect, dampening current fluctuations. The estimated residual standard deviation (/Sigma) was relatively small (0.00486, $p < 0.001$), indicating that the model explains a substantial portion of the variability in the differenced NPF series with limited unexplained noise. Overall, the results highlight that short-term changes in NPF are shaped more strongly by the adjustment effects of past shocks than by direct persistence from prior values.

Table 12. Estimation Results of the Loan-to-Deposit Ratio (LDR) Variable for BPR

D.LDR	Coef	Std. Err	Z	P>| Z |	95% Conf	Interval
Const	-.0002839	.0008842	-0.32	0.748	-.0020169	.0014491
ARMA						
AR						
L1	1.721938	.0347122	49.61	0.000	1.653903	1.789972
L2	-.9690643	.0289726	-33.45	0.000	-1.02585	-.9122791
MA						
L1	-1.812045	.0181073	-100.07	0.000	-1.847535	-1.776555
L2	.9999996	.	.	.	.	.
/Sigma	0.0126603	.0005501	23.02	0.000	.0115822	.0137384

Source: Researcher-processed data, 2024

Table 12 presents the estimation results of the ARMA model for the first-differenced loan-to-deposit ratio (D.ldr). The constant coefficient (_cons) was -0.0002839 with a p-value of 0.748, indicating that the constant was not statistically significant and did not have a meaningful influence on D.ldr. The autoregressive coefficient at lag one (AR L1) is 1.721938, with a highly significant p-value ($p < 0.000$), indicating a strong positive relationship between the current D.ldr value and its value in the previous period. This suggests that an increase in D.ldr in the prior period is likely to be followed by a further increase in the current period. In contrast, the lag two autoregressive coefficient (AR L2) is -0.9609643 and also statistically significant ($p < 0.000$), suggesting a strong negative effect from the D.ldr value two periods prior. This may reflect mean-reverting behavior in the series.

For the moving average (MA) components, the coefficient for MA L1 is -1.812045 with a p-value < 0.001, indicating that shocks from one period prior have a significant negative effect on the current value. Similarly, the MA L2 coefficient is -0.999996 and statistically significant, suggesting that residual errors from two periods ago also exert a strong influence on the current value. Lastly, the estimated standard error (sigma) was 0.0126603 with a p-value < 0.001, indicating that the model captured a significant portion of the variation in D.ldr. Overall, the ARMA model results revealed complex dynamic behavior in the D. ldr variable, with significant influences from both autoregressive and moving average components across multiple lags, reflecting strong persistence and feedback mechanisms in the data.

Table 13. Estimation Results of the Liquidity Variable for BPR

Liquidity	Coef	Std. Err	Z	P>| Z |	95% Conf	Interval
Const	.0093902	.0004006	23.44	0.000	.0086051	.0101753
ARMA						
AR						
L1	.8295787	.0910305	9.11	0.000	.6511623	1.007995
MA						
L1	-.2912653	.1113319	-2.62	0.009	-.5094718	-.0730589
/Sigma	.0009067	.0000265	34.25	0.000	.0008548	.0009586

Source: Researcher-processed data, 2024

Table 13 presents the estimation results of the ARMA model for liquidity. The constant coefficient is significantly positive (0.0093902, $p < 0.000$), indicating a strong baseline liquidity level in the model. The autoregressive coefficient at lag one (AR L1) is also significantly positive (0.8295787, $p < 0.000$), suggesting that an increase in liquidity in the previous period is followed by a further increase in the current period. This reflects a strong temporal dependence on liquidity behavior. Conversely, the moving average coefficient at lag one (MA L1) is negative and marginally significant (–0.2912653, $p < 0.09$), indicating that negative shocks or fluctuations in the previous period have a dampening effect on the current liquidity value.

The estimated standard error (sigma) is –0.0009067, which, despite its negative sign (likely due to model reporting conventions), reflects notable residual variability, suggesting that the model effectively captures the dynamics of the liquidity data. Overall, the ARMA model demonstrates a strong performance in explaining liquidity dynamics. These findings suggest that liquidity movements are not solely driven by current conditions but are also shaped by historical patterns, including persistent upward trends and corrective effects resulting from past shocks.

Table 14. Estimation Results of the Non-Performance Loan (NPL) Variable for BPR

D.NPL	Coef	Std. Err	Z	P>| Z |	95% Conf	Interval
Const	-.0002438	.0000371	-6.58	0.000	-.0003165	-.0001712
ARMA						
AR						
L1	.8002422	.0556946	14.37	0.000	.6910828	.9094016
MA						
L1	-.9999911	55.67628	-0.02	0.986	-110.1235	108.1235
/Sigma	.0025966	0.722469	0.04	0.486	0	.1441978

Source: Researcher-processed data, 2024

Table 14 presents the estimation results of the ARMA model for the first-differenced non-performing loan (D.npl) variable. The constant coefficient (_cons) is –0.0002438 with a highly significant p-value ($p < 0.000$), indicating that when other variables are held constant, the baseline change in D.npl is significantly negative. The autoregressive coefficient at lag one (AR L1) is 0.8002422 and is also highly significant ($p < 0.000$), suggesting a strong positive temporal relationship an increase in D.npl in the previous period tends to be followed by an increase in the current period. This highlights the persistent behavior of the D.npl trend over time.

In contrast, the moving average coefficient at lag one (MA L1) is –0.9999911, but it is statistically insignificant ($p = 0.986$), indicating that past residual errors have no meaningful influence on the current value of npl. The estimated standard error (sigma) was –0.0025966, with a p-value of 0.486, indicating non-significant residual variability. This suggests that the model may have limited explanatory power in capturing the overall variation in D.npl data.

Overall, the ARMA model results suggest that the movement of D.npl is primarily driven by its historical values, while random shocks or past errors do not appear to play a significant role. In other words, if there was an increase or decrease in D.npl in the prior period, that trend is likely to persist in the following period. However, the direction and magnitude of the change may still be influenced by external or unobserved factors that are not accounted for in the model.

4.4. Forecasting Test

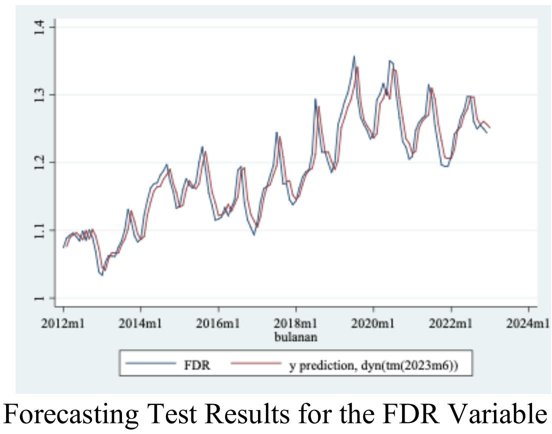

Figure 1. Forecasting Test Results for the FDR Variable of BPRS
Source: Researcher-processed data, 2024

Figure 1 illustrates that the forecast for the Financing-to-Deposit Ratio (FDR) variable is expected to remain stable over the next six months. This projection suggests that the FDR value will continue to hover near its maximum level, reflecting the sustained optimism of BPRS (Sharia Rural Banks) in their ability to distribute financing effectively. The continued stability of the FDR at a high level indicates that the BPRS can consistently channel third-party funds into productive financing activities. This reflects a high level of public trust, as evidenced by the substantial ratio of financing disbursed to the total funds collected.

Such consistency may also be interpreted as a reflection of effective risk management practices, particularly in maintaining a healthy balance between fund mobilization and disbursement, thereby minimizing liquidity risks. Furthermore, the persistently high FDR suggests that BPRS applies rigorous credit assessments and exercises prudence in financing decisions, which helps mitigate the risk of non-performing loans. This finding aligns with the principle of prudential banking, which is a fundamental pillar of Islamic financial institutions. In conclusion, the projected stability of the FDR not only signals operational optimism but also demonstrates the readiness and resilience of the BPRS in navigating future economic conditions. This reassures stakeholders that the intermediation function of BPRS remains healthy, stable, and sustainable.

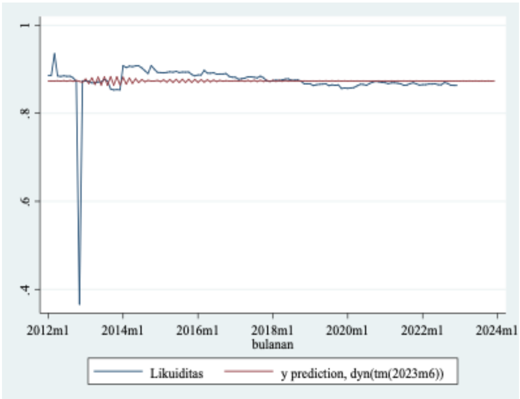

Figure 2. Forecasting Test Results for the Liquidity Variable of BPRS
Source: Researcher-processed data, 2024

The liquidity forecast illustrated in Figure 2 shows that the liquidity ratio of BPRS is expected to remain stable over the next six months, with no significant increases or decreases. This projection indicates that the BPRS consistently maintains its liquidity levels within an optimal range. The sustained stability of the liquidity ratio reflects the ability of BPRS to manage its current assets to meet short-term liabilities effectively. This resilience serves as an important indicator that the institution is capable of responding to sudden liquidity demands, whether from customer withdrawals or new financing needs. Furthermore, it points to the existence of sound internal policies that ensure a balanced composition of liquid assets and liabilities, thereby minimizing liquidity risk.

This condition also enhances the reputation of the BPRS as a prudent financial institution, reinforcing public trust. The ability to maintain adequate liquidity levels sends a positive signal to regulators and investors, demonstrating that BPRS has implemented strong financial governance and is well-prepared to navigate future economic fluctuations. In summary, the projection of a stable liquidity ratio suggests that BPRS is not solely focused on expanding financing activities but also remains committed to upholding prudential principles and ensuring long-term financial health.

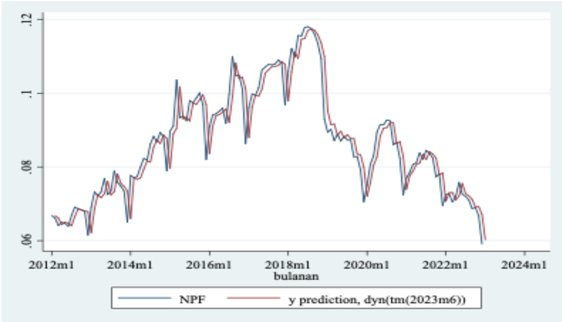

Figure 3. Forecasting Test Results for the NPF Variable of BPRS
Source: Researcher-processed data, 2024

The forecast of the Non-Performing Financing (NPF) variable suggests a downward trend over the next six months. This indicates that BPRS (Islamic Rural Banks) has the potential to reduce the level of financing risk, particularly in terms of non-performing financing or credit. The projected decline in NPF was strongly influenced by the persisting downward pattern in the historical data (time series), which reinforced the reliability of this trend. A decrease in NPF serves as a positive signal for the health of BPRS financing portfolios, as lower levels of problematic financing reflect improvements in asset quality. This trend can also be interpreted as the result of effective risk management practices, including more selective customer screening, improved post-disbursement monitoring, and enhancements in the restructuring processes for troubled financing.

Moreover, it demonstrates the ability of BPRS management to adapt to economic fluctuations and external challenges, such as the aftermath of the pandemic or volatility in the real sector. The consistent decline in NPF reinforces stakeholder and customer confidence in the capacity of BPRS to maintain financial stability and minimize credit risk-related losses. If this downward trend can be sustained, it is expected to contribute positively to the profitability and competitiveness of BPRS in the banking industry. Furthermore, it will support inclusive and sustainable economic growth through healthier and more productive financing distributions.

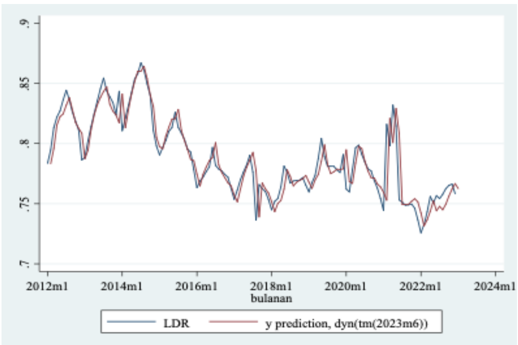

Figure 4. Forecasting Test Results for the LDR Variable of BPR
Source: Researcher-processed data, 2024

The forecast for the Loan-to-Deposit Ratio (LDR) variable, representing the credit disbursement ratio of BPR, as illustrated in Figure 4, shows a downward trend over the next six months. This trend suggests that BPR have begun to adopt a more cautious stance in their lending activities. The projected decline in the LDR ratio may reflect the strategic response of BPR management to rising credit risk amid ongoing economic uncertainties. By reducing the proportion of credit disbursed relative to third-party funds collected, BPR effectively limit their exposure to potential defaults, especially in light of concerns over borrower quality and liquidity constraints in the financial system. This prudent approach is typically implemented when banks anticipate a deterioration in creditworthiness or when market conditions indicate a tightening of liquidity. Additionally, the declining LDR trend may signal efforts by BPRs to strengthen their liquidity positions, ensuring greater capacity to meet short-term obligations and reinforce overall balance sheet resilience.

Although this strategy may temporarily slow the growth of the lending portfolio, it represents a measured and forward-looking decision aimed at preserving the financial stability. The selective tightening of credit disbursement aligns with the principles of prudential banking, emphasizing risk mitigation before a potential rise in non-performing loans (NPLs) occurs. In conclusion, the forecasted decrease in the LDR serves as a positive indication that BPRs are becoming more selective, adaptive, and risk-aware in their credit management practices, demonstrating their commitment to safeguarding financial health and maintaining customer trust in an uncertain economic environment.

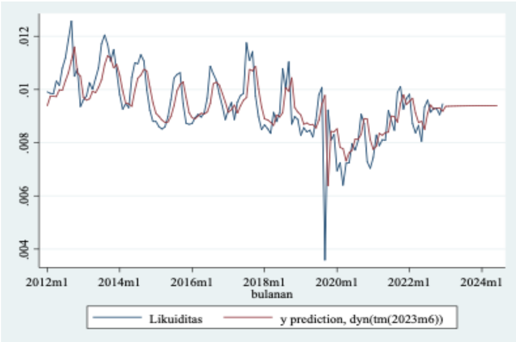

Figure 5. Forecasting Test Results for the Liquidity Variable of BPR
Source: Researcher-processed data, 2024

The liquidity variable is projected to decline over the next six months, indicating that BPR may face heightened vulnerability to liquidity risk, which could hinder its ability to fulfill its short-term obligations using current assets. A decrease in the liquidity ratio can result from lower ownership of liquid or current assets or from an increase in current liabilities that are not matched by a corresponding growth in current assets. This situation underscores the need for BPR to exercise greater prudence in managing its asset and liability structures to avoid a potential liquidity crisis that could disrupt overall banking operations in the future. Low liquidity levels may also undermine public confidence, as they signal that the bank may be less capable of meeting withdrawal demands, potentially triggering a bank run or large-scale fund withdrawals.

Additionally, reduced liquidity can limit an institution's flexibility to extend new loans or engage in profitable investments, thereby constraining growth opportunities. Given these risks, it is crucial for the BPR to reassess its balance sheet composition and strengthen its liquid asset reserves to ensure ongoing financial stability and maintain public trust. Furthermore, improving liquidity governance and implementing proactive risk management strategies are essential for BPR to remain resilient amid evolving market dynamics and potential macroeconomic pressures.

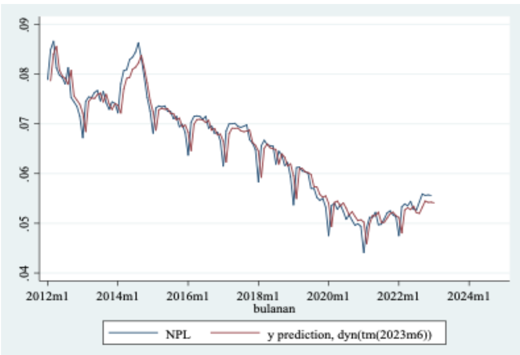

Figure 6. Forecasting Test Results for the NPL Variable of BPR
Source: Researcher-processed data, 2024

The forecast for the Non-Performing Loan (NPL) variable, as illustrated in Figure 6, shows a relatively stagnant trend, with no significant increase or decrease in the level of non-performing loans. This indicates that a substantial portion of borrowers continues to experience difficulties in meeting their repayment obligations. This stagnation suggests that the BPR has yet to fully optimize its credit disbursement practices, particularly in terms of borrower selection and creditworthiness assessment. The inability to reduce the NPL ratio reflects the limited effectiveness of current credit risk management strategies and may indicate weaknesses in post-disbursement monitoring and insufficient evaluation of credit portfolio performance.

Persistently high NPL levels pose a risk to bank profitability as they increase the need for loan loss provisions and reduce income from performing assets. Over time, this condition could erode stakeholder confidence, including that of depositors, regulators, and potential investors, thereby affecting the long-term sustainability of BPR operations. To address this issue, BPRs must strengthen borrower screening processes, enhance credit analysis frameworks, and implement stricter monitoring and supervision mechanisms to ensure that loan funds are used appropriately. In addition, establishing an early warning system for identifying potential problem loans, alongside efforts to build human resource capacity for risk management, is essential for sustainably improving asset quality.

4.5. Discussion

The analysis of financial risks in Islamic Rural Banks (BPRS) and Conventional Rural Banks using the ARIMA method provides a comprehensive understanding of the differences in their risk profiles and management practices. In developing economies, these two banking models often adopt distinct approaches to decision-making, fund allocation, and liquidity management. Conventional rural banks are generally more exposed to financial risks, particularly regarding liquidity and non-performing loans. A low liquidity ratio usually reflects an excessive concentration of funds in illiquid assets, which increases vulnerability when sudden funding pressures occur. Simultaneously, persistent credit risk remains a major challenge, as high levels of non-performing loans are often associated with weak governance, inadequate customer risk assessment, and limited loan loss reserves. These weaknesses collectively increase exposure to credit losses and reduce institutional resilience, especially in volatile macroeconomic environments (Widarjono, Anto, & Fakhrunnas, 2021; Widodo & Kurniawan, 2017).

Recent studies have shown that the differences in risk profiles between BPRS and conventional rural banks are increasingly influenced by the adoption of financial technology (FinTech). Al Hammadi, Jimber-Del Río, Ochoa-Rico, Montero, and Vergara-Romero (2024) highlight that the integration of FinTech in Islamic banking enhances financial stability by improving efficiency and strengthening risk management. However, Chazi, Mirzaei, and Zantout (2024) revealed that during the COVID-19 pandemic, Islamic banks experienced heightened liquidity risk and declining profitability, emphasizing the importance of robust risk management frameworks in times of crisis. Collectively, these findings underscore the need for adaptive and innovative strategies to enhance banking institutions' resilience in dynamic economic environments.

Complementing this perspective, ARIMA-based forecasts of loan-to-deposit ratios, non-performing loans, and liquidity indicate a slight but statistically insignificant decline in credit disbursement, accompanied by a downward trend in liquidity ratios. These results highlight the importance of the prudent allocation of third-party funds and the reinforcement of comprehensive risk management systems to mitigate emerging challenges. For conventional rural banks, this entails improving credit assessments, strengthening continuous monitoring, and increasing loan-loss reserves. Additional measures, such as portfolio diversification and operational efficiency improvements, are also essential to ensure long-term stability (Irfany & Ulhaqqi, 2023; Purwita, Fauzi, & Susanti, 2024; Ramadhani, Firdaus, Nurhayati, & Purwanto, 2025).

In contrast, the BPRS demonstrated distinct characteristics. Their relatively high liquidity ratios reflect consistent adherence to prudential principles, allowing them to meet their short-term obligations more effectively. BPRS also concentrates its fund distribution on financing the real sector, which supports productive activities but exposes them to higher risks during sectoral downturns. The forecasting results suggest that financing disbursement in BPRS will remain stable, supported by high liquidity levels and a declining trend in problematic financing. This highlights improvements in the governance of fund distribution and closer supervision of both prospective and existing financing customers, which can help mitigate future risks of non-performing financing (Jusuf & Widarjono, 2024; Purwita et al., 2024; Widarjono, Wijayanti, & Suharto, 2022).

These results align with earlier findings that stress the importance of liquidity management and prudent fund allocation for maintaining stability in Islamic rural banks. Jusuf and Widarjono (2024) show that higher liquidity levels enhance the ability of Islamic rural banks to withstand sudden withdrawals and external shocks, confirming that liquidity acts as a buffer against sectoral volatility. However, other studies note that despite strong liquidity, BPRS remain vulnerable to sector-specific risks, particularly when financing is concentrated in industries such as agriculture and small-scale enterprises (Widarjono et al., 2022). Meanwhile, research on conventional rural banks suggests that portfolio diversification and broader sectoral engagement can reduce exposure to non-performing loans more effectively than Islamic rural banks, whose lending practices are constrained by Sharia principles (Irfany & Ulhaqqi, 2023). These similarities and differences indicate that while liquidity and supervision are vital for BPRS, both types of banks must continuously adapt their frameworks to keep pace with shifting economic dynamics.

The comparison between the BPR and BPRS underscores the importance of designing risk mitigation strategies tailored to the unique characteristics of each model. Conventional rural banks must strengthen credit governance and liquidity management, whereas Islamic rural banks should enhance the oversight of real sector financing and refine customer selection practices. Practically, these insights offer valuable guidance for bank managers and regulators in shaping policies that reinforce the resilience of Indonesia's microbanking sector. Academically, this study contributes to the literature on comparative risk management in microbanks and opens pathways for further research on external factors such as regulatory reforms, macroeconomic conditions and customer behavior (Bashir & Azeez, 2022; Elgharbawy, 2020).

Broader evidence also points to both convergence and divergence in the risk management approaches of Islamic and conventional banks. Elgharbawy (2020) finds that while both systems employ various risk management tools, Islamic banks tend to adopt more conservative practices owing to Sharia requirements, particularly in credit evaluation and asset quality control. Nevertheless, Bashir and Azeez (2022) argue that despite these conservative approaches, Islamic banks remain vulnerable to operational risks, especially when their portfolios are highly concentrated in certain sectors. In the Southeast Asian context, other studies have highlighted that regulatory reforms and digital innovations play an increasingly crucial role in strengthening resilience in both systems, suggesting that external forces may sometimes have greater influence than internal policies. Together, these studies reinforce the importance of continuously adapting risk management frameworks to evolving regulatory, technological and macroeconomic conditions.

Overall, the findings confirm that the financial risk challenges in BPR and BPRS are structurally distinct and require context-specific responses. Strengthening risk management frameworks, adapting internal policies, and enforcing rigorous supervision are essential for sustaining microbanking operations. In addition, enhancing human resource capacity is crucial for timely response to evolving risks and regulatory demands. Finally, developing innovative financial products tailored to the needs of micro and small businesses is vital for expanding their market reach and reducing portfolio concentration risk.

5. Conclusions

5.1. Conclusion

Based on the analysis and discussion, we conclude that Islamic and conventional rural banks exhibit distinct financial risk profiles. Conventional banks generally face higher risks related to liquidity and non-performing loans, while Islamic banks tend to maintain healthier liquidity levels but still carry risks associated with nonperforming financing. Despite these challenges, both types of banks actively implement risk-mitigation strategies through different approaches to fund allocation and asset management. These findings highlight the need to strengthen risk management practices and tailor internal policies to the unique characteristics of each bank to ensure financial stability and sustainable business growth.

The practical contribution of this study lies in providing comprehensive insights into improving financial risk management in Islamic and conventional rural banks. For bank managers, the findings emphasize the importance of strengthening credit governance, enhancing liquidity management, and diversifying portfolios to ensure greater financial resilience. For regulators, this study highlights the need to design tailored supervisory frameworks and adaptive policies that accommodate the distinct characteristics of both banking models while safeguarding financial stability. From an academic perspective, this study enriches the comparative literature on Islamic and conventional microbanks and serves as a foundation for further studies exploring the impact of regulatory shifts, macroeconomic dynamics, and customer behavior on risk management practices.

5.2. Implications

5.2.1. Managerial Implications

The results highlight the need for bank managers to strengthen their internal risk management frameworks, particularly in credit governance, liquidity monitoring, and portfolio diversification. Conventional rural banks should focus on improving loan quality through rigorous customer assessment, ongoing monitoring, and adequate provisioning for loan losses. Meanwhile, Islamic rural banks are encouraged to enhance the supervision of real sector financing and implement stricter criteria for customer selection to reduce the likelihood of non-performing financing. In addition, both banking models should invest in human resource development and adopt innovative financial products tailored to the needs of micro and small business owners to strengthen their competitiveness and ensure long-term sustainability.

5.2.2. Policy Implications

For regulators, the findings underscore the importance of designing policies that are responsive to the distinct characteristics of Islamic and conventional rural banks. Regulatory authorities should establish adaptive supervisory frameworks that encourage prudent liquidity management, reinforce credit risk control, and ensure the resilience of microbanking institutions in volatile economic conditions. Furthermore, developing supportive policies, such as incentives for portfolio diversification, frameworks for Sharia-compliant financial innovation, and mechanisms for strengthening early warning systems, can enhance overall financial stability. By tailoring regulations to the unique operational models of each bank, policymakers can foster a more inclusive and sustainable rural-banking sector.

5.3. Limitation For Future Research

This study had several limitations. First, the analysis is limited to a small set of key quantitative variables liquidity ratios, Loan-to-Deposit Ratio (LDR), and Non-Performing Loans/Financing (NPL/NPF) without incorporating qualitative factors or managerial practices that can also significantly impact bank risk profiles. Second, the study relies solely on historical data from a specific period, which restricts its ability to capture the effects of macroeconomic shifts, regulatory changes, or extraordinary events, such as financial crises, occurring outside the sample timeframe. Furthermore, the ARIMA method primarily models past trends, making it less effective in anticipating sudden structural breaks or shocks. Therefore, the findings should be viewed as preliminary insights and warrant further investigation using broader datasets, additional variables, and complementary analytical approaches for a more robust understanding of the subject.

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