Economic Journal of Emerging Markets, 17(2) 2025, 191-206

EJEM
Econ.J.Emerg.Mark.

Economic Journal of Emerging Markets
Available at https://journal.uii.ac.id/jep

Measuring Islamic Banking resilience: A case study of *Nusa Tenggara Barat* Province, Indonesia

Dimas Bagus Wiranatakusuma[1]*, Anggi Aprizal[2]

[1]Economics Study Program, Faculty of Economics and Business, Universitas Muhammadiyah Yogyakarta, Yogyakarta, Indonesia
[2]Postgraduate Program, Universitas Muhammadiyah Yogyakarta, Yogyakarta, Indonesia
*Corresponding author: dimas_kusuma@umy.ac.id

Article Info

Article history:
Received 06 November 2024
Accepted 26 March 2025
Published 28 October 2025

JEL Classification Code:
E5, G2

Author's email:
anggi.aprizal.psc23@mail.umy.ac.id

DOI:
10.20885/ejem.vol17.iss2.art6

Abstract

Purpose — Islamic banks in *Nusa Tenggara Barat* (NTB) province have experienced positive developments in assets, branches, and financing. This study aims to measure the resilience of Islamic banking in NTB using a composite bank variable and to determine how effectively the institution manages and absorbs various risks.

Method — The data used consisted of monthly data from 2010 to 2023, covering several banking variables, including the Financing to Deposits Ratio (FDR), Non-Performing Financing (NPF), Bank Size (BS), and Third-Party Fund (TPF). The analysis method employed in this study was the early warning system (EWS), utilising a non-parametric signal extraction approach.

Findings — All selected banking variables are used to measure the resilience of Islamic banking in NTB through the composite index of bank (CIB). The signal extraction method provides optimal thresholds for each selected banking variable and for the composite index (CIB). Visualisation results show the interval values that can absorb risk and maintain the resilience of Islamic banking as follows: (1) FDR between 81% and 102%; (2) NPF between 1.29% and 1.89%; (3) BS between 3.79% and 4.59%; (4) TPF between 4.16% and 4.58%; and (5) CIB between 10.66 and 28.14.

Implications — Assessing the resilience of Islamic banking in NTB involves identifying key banking variables to pinpoint sources of risk exposure, determining the optimal time horizon for policy interventions, and setting appropriate thresholds for the surveillance mechanism.

Originality — Currently, the resilience of Islamic banks at the provincial level has not been widely studied, particularly in NTB Province, where there has been a notable increase in the number of Islamic banking offices and assets.

Keywords — Islamic banking, resilience, optimal thresholds, optimal time horizon, early warning system approach

Introduction

As a country that adheres to the concept of an open and developing economy, Indonesia has been significantly affected by external shocks, including financial crises, since the 1990s. The two major financial crises were the Asian Financial Crisis (AFC) in 1998 and the Global Financial Crisis (GFC) in 2008 (Azwar & Tyers, 2015). Since then, Islamic banks in Indonesia have continued to grow. At

P ISSN 2086-3128 | E ISSN 2502-180X
Copyright © 2025 Authors. This is an open-access article distributed under the terms of the Creative Commons Attribution-ShareAlike 4.0 International License (http://creativecommons.org/licences/by-sa/4.0/)

the provincial level, the development of Islamic banks has shown significant growth, as reflected in the increases in each Islamic bank's total assets across provinces. Jakarta became a special province, with assets increasing from IDR 491 billion in August 2022 to IDR 554.913 billion in August 2023, a 13% increase. In addition, of the ten provinces that dominate Islamic banking assets nationally, nine of them come from provinces located in the islands of Java and Sumatra. In this case, *Nusa Tenggara Barat* (NTB) is the only province outside the two islands to compete, with asset growth from IDR 20 billion in August 2022 to IDR 22 billion in August 2023, a 10% increase. This indicates that NTB Province can compete with the larger provinces on the two main islands, despite its smaller area and lower economic resources.

In addition to assets, Islamic banks in NTB have also experienced positive developments in terms of branch offices and financing. From 2018 to 2022, the number of Islamic banks' branches in NTB increased from 41 in the first quarter of 2018 to 72 in the fourth quarter of 2022, a 43% increase. Meanwhile, Islamic banks' financing in NTB increased from IDR 132 billion in August 2022 to IDR 189 billion in December 2023, reflecting an increase of 23% in 2023. This development indicates that the regional economy is showing a positive trend and that operational risks of banking are well controlled, allowing Islamic banks to gradually expand their branch networks.

In terms of risk management, several main risk assessments conducted by Bank Indonesia (BI) of Islamic banks focus on financing and liquidity risks. In terms of financing, in the first quarter of 2021, the Non-Performing Financing (NPF) rate of Islamic banks in NTB decreased from 1.71% to 1.32% in the first quarter of 2022. In comparison, in terms of liquidity, in the first quarter of 2021, the Financing to Deposit Ratio (FDR) decreased from 104.98% to 98% in the first quarter of 2022. Although the NPF level remains ideal under Central Bank regulations, the FDR is still less than ideal. A decrease in FDR aligns with the slow regional economic growth.

The relatively low regional economic growth conditions indicate the need for greater support from the Islamic banking sector in encouraging the development of the real sector in NTB. However, the presence of financing and liquidity risks in Islamic banks requires greater attention, as they create obstacles and undermine resilience in banking operations. Technically, the strength of Islamic banking is in an ideal condition, where some selected banking variables, such as the Non-Performing Financing ratio and financing to deposit ratio, remain within the tolerance thresholds of Bank Indonesia (BI) around a maximum of 2% - 5% and 78-92%, respectively (Bank Indonesia, 2015). Thus, any movement of the selected variable serves as a signal of the banking sector's resilience, reflecting the escalation of risk during banking operations.

Banking sector resilience can be defined as the ability of the banking sector to survive and adapt to both short- and long-term shocks while continuing to fulfil its role in supporting real economic growth (Caldera-Sánchez, 2017; Wiranatakusuma, 2018). Unfortunately, current studies on the resilience of Islamic banks mainly discuss issues on a national and international scale (Maliha & Marlina, 2019; Khan et al., 2019; Pratama & Rizal, 2019; Setyawati et al., 2019; Ghosh et al., 2020; Nugroho et al., 2020; Ahmad et al., 2022; Setyawati et al., 2022; Fitri & Hafiz, 2022; Albaity et al., 2023). Meanwhile, the resilience of Islamic banks within the provincial scope has not been widely studied, especially in NTB Province.

Therefore, this study focuses on the resilience of Islamic banking in NTB by adopting several selected banking variables. The significance of this study lies in selecting leading variables, calculating optimal thresholds, selecting optimal time horizons for all variables, and comparing them with existing regulations and ongoing data. Those attempts finally enable banking practitioners and policymakers to implement surveillance mechanisms as part of a significant effort to achieve and maintain financial system stability.

Methods

This quantitative study analysed the resilience of Islamic banks in West Nusa Tenggara Province from 2010 to 2023, using secondary data from the Financial Services Authority (OJK). The sample period spanned January 2010 to August 2023, utilising four variables: Financing-to-Deposit Ratio (FDR), Non-Performing Financing (NPF), Bank Size (BS), and Third-Party Fund (TPF).

The data were analysed using the early warning system (EWS) method with a signal extraction approach. Technically, the analysis was conducted in Excel 365 using the Islamic Banking Resilience Index (IBRI) modelled by Wiranatakusuma (2018).

The study involved 15 sequential steps to select the leading variables, calculate the optimal threshold, and select the optimal time horizon (Figure 1).

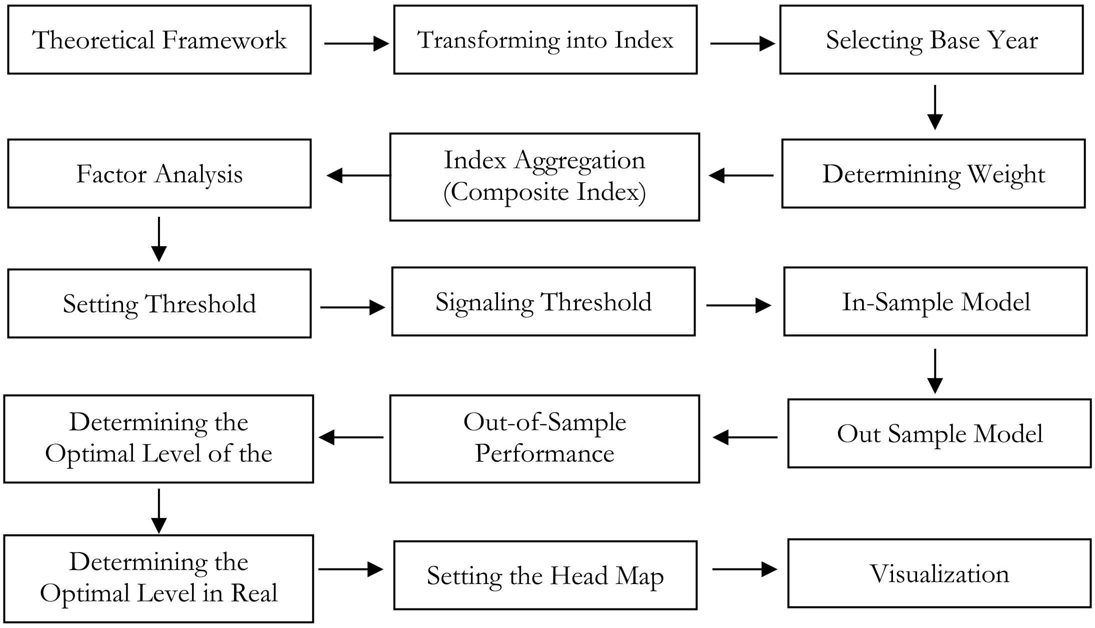


Figure 1. Stages of the early warning system (EWS) method
Source: Modified from Kaminsky and Reinhart (1999)

Transforming Into an Index

Index data provide a numerical method for measuring relative changes across variables over time, simplifying data by converting absolute values into relative figures. In this study, index data were used to evaluate the resilience of Islamic banking, with normalisation required to standardise units across variables.

$$I_{it} = \frac{(Xit - \bar{X}i)}{\sigma i} \tag{1}$$

where:
I_{it}= The single index value of variable i at time t.
X_{it}= The value of variable i at time t.
$\bar{X}i$ = The mean value of variable i.
σi = Standard deviation of variable i.

Selecting The Base Year

The base year is the year used as a benchmark or reference when collecting, combining, or analysing data. The selected year is considered the base year, in which there is a fundamental balance and the smallest possible deviation across all index data.

$$S = \sqrt{\frac{1}{N-1} \sum_{i}^{N}, (X_t - \bar{X})^2} \tag{2}$$

Where: S = Standard deviation; Xt = Value of each observation in the sample; X = Sample mean in the base year; N = Number of observations in the sample

$$\bar{X} = \frac{\sum X}{N} \tag{3}$$

Where: X = Sample mean for the base year; $\sum x$ = Number of X values in the sample; N = Number of values in the sample

Determining Weight

The weighted average method assigns each variable a weight reflecting the importance of the parameter it proxies. A higher weight indicates that the role of the variable is becoming increasingly essential in establishing the resilience of Islamic banking.

$$Weighted\ Index_{ij} = \frac{\text{Average of Varianceij}}{Total\ Variance} \tag{4}$$

Aggregate Index (Composite index)

An aggregate or composite index is an index created by combining several measures to capture a broader concept or phenomenon. In this study, one composite index was determined by including four single indices with the formula:

$$\text{Composite Index}_t = w * IFDR_t + w * INPF_t + w * IBS_t + w * ITPF_t \tag{5}$$

Where: I = Variable index, w = Weighted index, t = Time observation

Factor Analysis

This study uses factor analysis to test data and variable coherence, ensuring consistency in relationships and meeting research objectives to produce reliable results (Saaty, 1990). The Hierarchical Consistency Ratio (HCR) was used to prioritise variables in the composite index and to assess coherence, with an ideal HCR of 0.1 or less (10%).

$$HCR = CI\ RI \tag{6}$$
$$CI = \lambda maks - n\ n - 1 \tag{7}$$
$$RI = 1.98 * (N - (n - 1))\ N \tag{8}$$

Where: CR = Consistency ratio; CI = Consistency index; RI = Random index; N : Number of criteria or sub-criteria

The value of the random index can be determined directly from the random index table. In this study, four variables were used, yielding a random index value of 0.9 (Table 1).

Table 1. Random index values.

N	2	3	4	5	6	7	8	9	10
RI	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Source: Saaty (1990)

Setting Threshold

Evaluating financial institutions, identifying crises, analysing risks, and setting priorities requires a threshold to filter out less impactful decisions. The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method is effective for analysing interrelated problems by categorising them into causal and effect groups (Fu et al., 2017; Shakeri et al., 2021). DEMATEL clarifies cause-and-effect relationships, reduces complexity, and provides objective recommendations (Seker & Zavadskas, 2017). In this study, DEMATEL-generated thresholds were used to assess Islamic banking resilience (Kaminsky & Reinhart, 1999). Its systematic methodology prioritises criteria based on direct and indirect effects, thereby enhancing the trustworthiness of decision-making (Özdemirci et al., 2023). Before using the DEMATEL method, it is necessary to find the causal relationship of all variables using the Granger Causality method (Granger, 1969) (Table 2).

Table 2. Criteria for the DEMATEL method and Granger causality

DEMATEL Scale	Criteria	Granger Causality
1	Low Influence	>10%
2	Medium Influence	5%-10%
3	High Influence	1%-5%
4	Very High Influence	<1%

Source: Granger (1969), Gabus and Fontela (1973)

$$\alpha = \frac{\sum_{t=1'}^{n} \sum_{j=1'}^{n} [t_{ij}]}{N} \tag{9}$$

$$Ri = \left[\sum_{j=1}^{n} t_{ij}\right] n * 1 = [ti\ ]n * 1 \tag{10}$$

$$Cj = \left[\sum_{i=1}^{n} t_{ij}\right] n * 1 = [ti\ ]n * 1 \tag{11}$$

Where:
α = Threshold value
Ri = Row in matrix T
Cj = Column in matrix T
I = DEMATEL Scale Row
J = DEMATEL Scale Column

Signalling Threshold

The signalling threshold is part of the early warning system (EWS), which helps detect potential vulnerabilities in the economy. This signalling threshold was implemented by assigning codes 0 and 1 to selected variables in a given month based on the calculated threshold multiplier (Berg & Pattillo, 1999). To carry out threshold signalling, consider the following criteria (Table 3).

Table 3. Threshold signaling

Threshold	Criteria Index for a Certain Variable (l_{it})	Signal
Upper	= l_{it} > Threshold Multiplier Value	1 (Yes)
	= l_{it} < Threshold Multiplier Value	0 (No)
Lower	= l_{it} < Threshold Multiplier Value	1 (Yes)
	= l_{it} > Threshold Multiplier Value	0 (No)

Source: Kaminsky and Reinhart (1999), Berg and Pattillo (1999)

In-Sample Model

The in-sample model calculates the estimated trend of Islamic banking resilience using the Hodrick-Prescott filter. The HP separates cycle components of optimising the loss function (Kanas et al., 2012). In the Early Warning System (EWS) approach, setting the lambda (λ) value is critical, as it influences prediction accuracy across different time horizons (e.g., 12 or 24 months) (Kaminsky & Reinhart, 1999; Ravn & Uhlig, 2002; Domala & Kim, 2023). The λ function, a smoothing parameter, was applied as per Ravn and Uhlig (2002)'s formula:

$$\text{Lambda } (\lambda) = (14.400 * (\text{Number of Observations in One Month}))^2 \tag{12}$$

Out Sample Model

The Out Sample Model was conducted using the crisis-signal matrix framework, or early warning system (EWS), to evaluate the previous signals. In the crisis-signal matrix framework, A is the number of months the variable produces a good signal, B is the number of months the variable produces a bad signal because it sends a false signal, C is the number of months the variable fails to issue a warning signal, and D is the number of months when the variable does not give a signal or there is no crisis (Table 4) (Kaminsky & Reinhart, 1999).

Table 4. True and false signal assessment using the crisis-signal matrix

Items	Stress occurs in the next n months (C = 1) (Pre-stress periods)	No stress occurs in the next n months (C=0) (Pre-stress periods)
Signal (S=1)	A (Number of true imbalance signals)	B (Number of true imbalance signal types two error)
No Signal (S=0)	C (Number of false balance signals- types one error)	D (Number of true balance signals-)

Out Sample Model Performance

At this stage, the selection of the best time horizon was taken as the one with the least Quadratic Probability Score (QPS), representing accuracy, and the Global Square Bias (GSB), representing calibration. The QPS and GBS values range from 0 to 2, where 0 represents perfect accuracy or calibration. The robustness analysis in this study relies on the out-of-sample performance stage to evaluate the reliability of the early warning system model. Accuracy refers to whether forecasted values are sufficiently accurate to reflect the reality being captured and to the closeness of computations or estimates to exact values (Kaminsky & Reinhart, 1999; Berg & Pattillo).

Determining the Optimal Level of Index Value

This stage aims to assess variable index values within optimal, tolerant, stagnant, or vulnerable conditions, with "optimal" as the most preferred state. A condition reflects each variable's characteristics, with "High is Good" for FDR, BS, and TPF. At the same time, "Low is Good" applies to NPF in the Islamic banking sector (Table 5).

Table 5. Definition of optimal, tolerant, stagnant, and vulnerable conditions

A Variable with the Characteristic of "High is Good."	
Optimal	Average ≤ Variable ≤ Upper Threshold
Tolerance	Average > Variable ≥ Lower Threshold
Stagnant	Variable > Upper Threshold
Vulnerability	Variable < Lower Threshold
A Variable with the Characteristic of "Low is Good."	
Optimal	Average ≥ Variable ≥ Lower Threshold
Tolerance	Average < Variable ≤ Upper Threshold
Stagnant	Variable < Lower Threshold
Vulnerability	Variable > Upper Threshold

Calculating the Optimal Level in Real Value

After finding the best model for calculating the resilience of Islamic banking using index data, the next step was to convert the model back to the original data.

Using the Head Map

A head map is a data visualisation method that uses different colour representations to display data conditions. The use of various colours enables the identification of the sources of vulnerabilities affecting the resilience of Islamic banking (Table 6).

Table 6. Use of colours in the head map

Vulnerable/Excessive
Tolerance/Healthy Enough
Expected/Optimal/Healthy
Stagnant/Strict/Prudent

Visualisation

The visualisation stage can present research results effectively and make them easier to understand by summarising the key points.

Results and Discussion

The resilience analysis of Islamic banking in West Nusa Tenggara Province began with assessing financial performance metrics, including FDR, NPF, BS, and TPF, which represent banking vulnerabilities. These variables reflect liquidity risk (FDR), credit risk (NPF), market risk (BS), and operational risk (TPF). The next step was to determine the threshold ranges (optimal, tolerant, stagnant, and vulnerable) for each variable to gauge resilience. For "high is good" variables, the optimal range lies between the average and upper threshold; for "low is good" variables, it lies between the average and lower threshold. An Early Warning System (EWS) approach with signal extraction was used to assess the resilience level of each variable.

Transforming into index data is intended to facilitate measuring relative changes, comparing variables or groups, analysing, providing baselines, and measuring relative performance. The following is a detailed explanation of the data from each variable of Islamic banking after converting absolute data into index data (Figure 2).

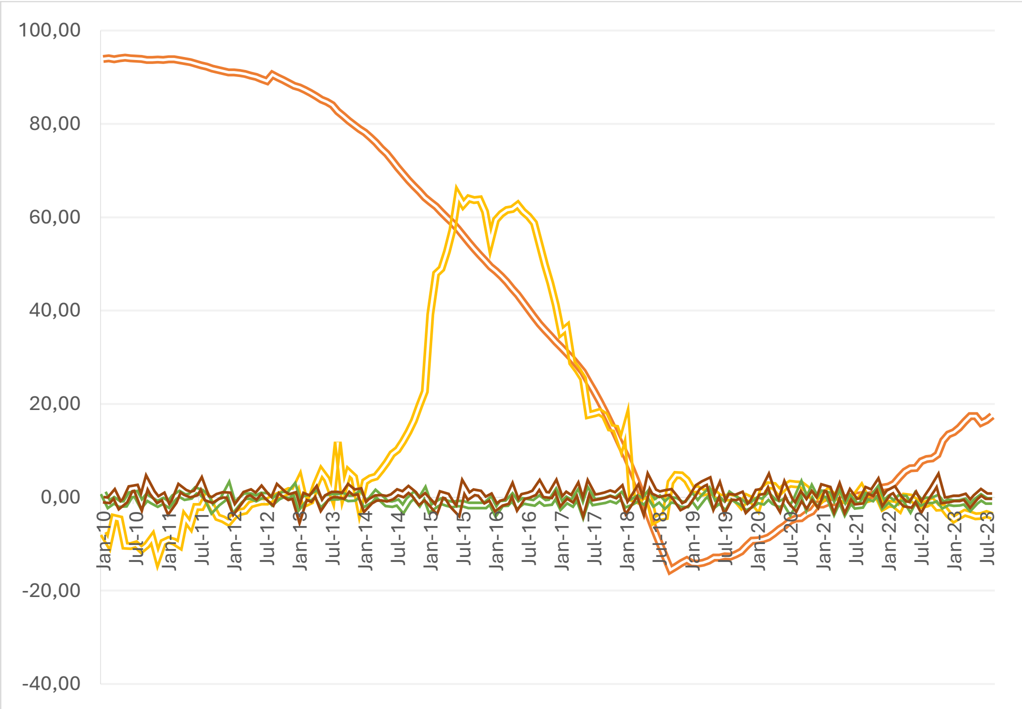


Figure 2. Transformation of Islamic banking index, where: Blue is NPF, Orange is FDR, Red is BS, Green is TPF,

The base year, selected as the year with the smallest standard deviation for each variable, was used as a benchmark or reference for analysing the data (Table 7).

Table 7. Selected base years

Sharia Bank Variables	Base Year
FDR	2021
NPF	2021
BS	2015
TPF	2014

Source: Processed Data, Excel 365

Determining the weight of each variable aimed to provide a relative value to each variable. Determining the weight demonstrates the more critical variables and their greater contribution to the formation of banking resilience (Table 8).

Table 8. Weight of Each Variable (Decimal)

Variable	FDR	NPF	BS	TPF
Weight	0.156	0.642	0.187	0.015

Source: Processed Data, Excel 365

The creation of a composite index in this study involved combining several variables to measure a broader concept or phenomenon (Figure 3). This composite index was created by combining several variables into a simpler, easier-to-understand aggregate measure. In calculating the composite index, the formula is as follows:

$Composite\ Bank\ Index\ (CIB)_t = w * IFDR_t + w * INPF_t + w * IBS_t + w * ITPF_t$

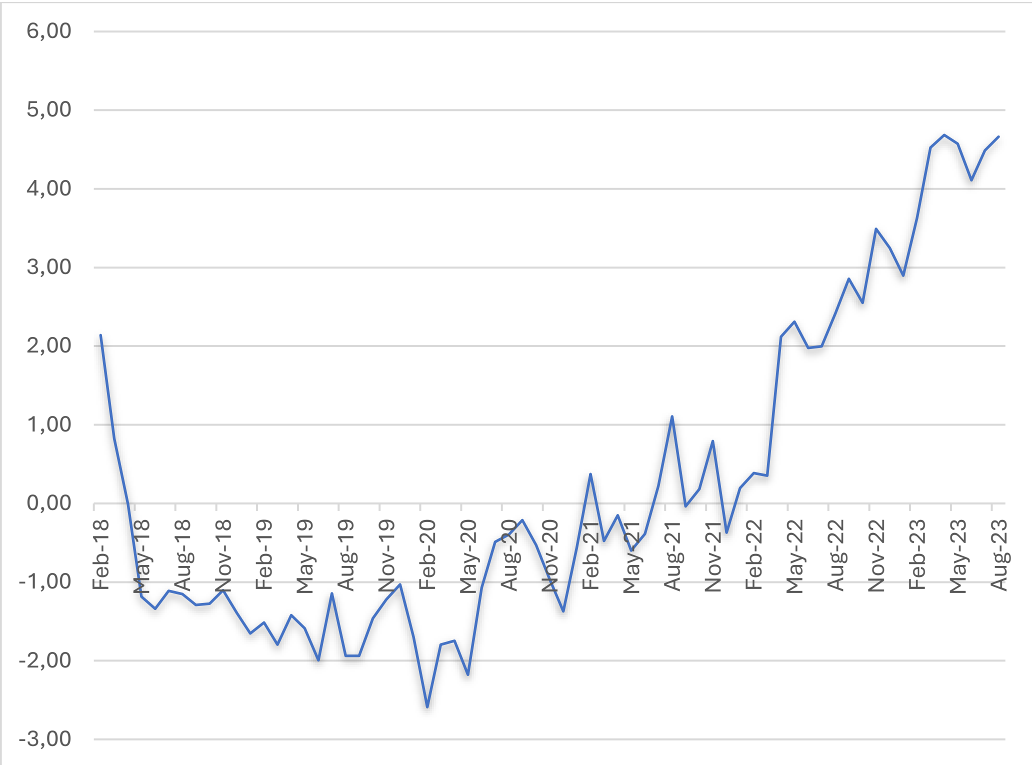


Figure 3. Composite Islamic Source: Processed Data, Excel 365
Where: Blue is the Composite index

The factor analysis test was based on the degree of coherence between the data and the variables. A good level of coherence between variables can be indicated by an R-value of no more than 0.1 (10%). The HCR values of Islamic banking in West Nusa Tenggara were 7%. This indicates that all variables were logically and consistently connected, with no contradictions in the research results (Table 9).

Table 9. Factor analysis

Factor Analysis	Sharia Bank
Consistency Index (CI)	0.16
Random Index (RI)	1.51
Consistency Ratio (CR)	0.11
HCR (Hierarchy Consistency ratio)	7%

Source: Processed by Author

The multiplier threshold was determined based on the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method. This DEMATEL method converts Granger causality values between variables into the DEMATEL scale to address the core problems of complex systems and facilitate decision-making. The value of the threshold calculation was used as the signalling threshold. The results of the calculations in this study were 0.74 for Islamic banking.

At the signalling stage, the threshold was determined by assigning codes 0 and 1 to the index variables for a given month based on the calculated multiplier threshold. Code 0 indicates optimal conditions or values within the ideal threshold, and code 1 indicates values outside the ideal threshold. In addition, this stage is intended to detect threats earlier, provide warnings, and enable rapid preventive or mitigating actions. The upper threshold is 1.20, and the lower threshold is -1.20 (Table 10).

Table 10. Signalling threshold variables of Islamic Banking in January 2018

Base Year/Month	Upper IFDR	Multiplier Threshold	Signal	Base Year	Lower IFDR	Multiplier Threshold	Signal
January 2018	8.59	1.20	1	January 2018	8.59	-1.20	0
Base Year/Month	Upper INPF	Multiplier Threshold	Signal	Base Year	Lower INPF	Multiplier Threshold	Signal
January 2018	0.59	1.20	0	January 2018	0.59	-1.20	0
Base Year/Month	Upper IBS	Multiplier Threshold	Signal	Base Year	Lower IBS	Multiplier Threshold	Signal
January 2018	-1.44	1.20	0	January 2018	-1.44	-1.20	1
Base Year/Month	Upper ITPF	Multiplier Threshold	Signal	Base Year	Lower ITPF	Multiplier Threshold	Signal
January 2018	-2.26	1.20	0	January 2018	-2.26	-1.20	1

Meanwhile, the in-sample model stage was carried out by assigning 0 or 1 to the Hodrick-Prescott (HP) Filter data or to the index variable forecast data for a given month, based on the multiplier threshold value (Table 11). The goal was to calculate the long-term trend of the operational resilience cycle of Islamic banking. Codes 0 and 1 indicate the degree of data suitability with the cycle trend: code 0 indicates the condition of the variable is at the ideal threshold, and vice versa for code 1. The in-sample model is said to be good if it can predict the amount of data in the future and has a goodness-of-fit model close to 0.

Table 11. In-sample model of Islamic Banking variables

Base Year/Month	Upper HP IFDR	Multiplier Threshold	Signal	Base Year	HP Lower HP IFDR	Multiplier Threshold	Signal
January 2018	19.01	1.20	1	January 2018	19.01	-1.20	0
Base Year/Month	Upper HP INPF	Multiplier Threshold	Signal	Base Year	Lower HP INPF	Multiplier Threshold	Signal
January 2018	1.80	1.20	1	January 2018	1.80	-1.20	0
Base Year/Month	Upper HP IBS	Multiplier Threshold	Signal	Base Year	Lower HP IBS	Multiplier Threshold	Signal
January 2018	-0.78	1.20	0	January 2018	-0.78	-1.20	0
Base Year/Month	Upper HP ITPF	Multiplier Threshold	Signal	Base Year	Lower HP ITPF	Multiplier Threshold	Signal
January 2018	0.40	1.20	0	January 2018	0.40	-1.20	0

This out-sample stage was carried out to evaluate the previous signalling using the signal-crisis matrix framework. The evaluation was conducted by summing the number of months of which indicators produced positive or correct signals (A), negative or incorrect signals (B), failed to provide warning signals (C), or did not provide signals or were not in crisis (D). The determination of this crisis signal was based on time horizons of 1, 3, 6, 12, and 24 months (Table 12).

Table 12. Evaluation of signalling based on the time horizon

Time Horizon		Upper				Lower			
		A	B	C	D	A	B	C	D
FDR	1 Month	106	20	0	37	3	11	19	130
	3 Months	104	20	0	37	3	11	19	128
	6 Months	101	20	0	37	3	11	19	125
	12 Months	95	20	0	37	3	11	19	119
	24 Months	83	20	37	37	3	11	107	107
NPF	1 Month	63	15	12	73	43	17	8	95
	3 Months	63	15	12	71	41	17	8	95
	6 Months	63	15	12	68	38	17	8	95
	12 Months	63	15	12	62	32	17	8	95
	24 Months	63	15	12	50	21	16	8	95
BS	1 Month	0	0	6	157	0	0	55	108
	3 Months	0	0	6	155	0	0	54	107
	6 Months	0	0	6	152	0	0	53	105
	12 Months	0	0	6	146	0	0	50	102
	24 Months	0	0	4	136	0	0	47	93
TPF	1 Month	0	0	35	128	0	0	26	137
	3 Months	0	0	35	126	0	0	25	136
	6 Months	0	0	33	125	0	0	25	133
	12 Months	0	0	32	128	0	0	24	128
	24 Months	0	0	30	110	0	0	23	117
CIB	1 Month	88	12	6	57	2	19	12	130
	3 Months	88	12	6	55	2	17	24	127
	6 Months	88	12	6	52	2	17	12	127
	12 Months	88	12	6	46	2	17	10	123
	24 Months	78	12	6	44	2	17	10	111

Table 12 evaluates the crisis-signalling effectiveness of key Islamic banking variables across multiple time horizons (1, 3, 6, 12, and 24 months). The variables assessed were FDR, NPF, BS, TPF, and the Composite Bank Index (CIB), each categorised as accurate imbalance signals (A), false signals (B), missed signals (C), and proper balance signals (D).

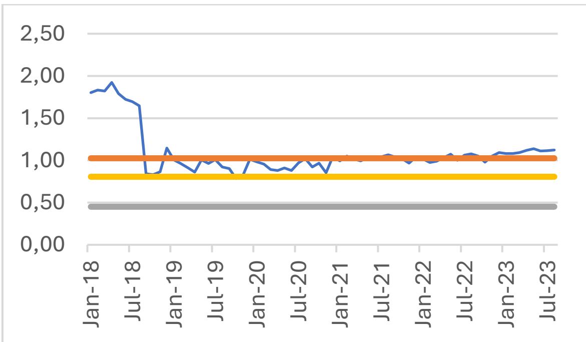
FDR's effectiveness declined with time; it provided 106 correct signals at a 1-month horizon, dropping to 83 at 24 months, while false signals remained stable at 20 across horizons. NPF produced stable, correct signals (around 63) for up to 12 months, declining slightly to 50 at 24 months. BS and TPF were less effective overall, generating minimal positive signals and mainly producing accurate balance signals, especially in shorter horizons. The CIB showed a decrease in positive signals with longer horizons, indicating that a combined index offers a broad perspective but with declining accuracy over time. In summary, FDR and NPF were more effective for short-term imbalance detection, whereas BS and TPF lacked sensitivity in both the short and long term. The CIB, while helpful, also saw reduced effectiveness over time. This indicates that FDR and NPF are exceptionally responsive to resilience challenges in NTB's Islamic banking, whereas BS and TPF, though cautious, require closer monitoring for early warning.

The out-sample performance stage assessed the prior signalling threshold, and the in-sample model stages were evaluated using the crisis-signal matrix framework. Out-sample model results identified crisis signals based on the optimal time horizon and the smallest Quadratic Probability Score (QPS) for accuracy or the smallest Global Square Bias (GSB) for calibration. The out-of-sample model results are used to detect crisis signals by determining the optimal time horizon, focusing on the minimal Quadratic Probability Score (QPS) for accuracy assessment or the minimal Global Square Bias (GSB) for calibration. This methodology guarantees that the constructed index accurately reflects the dynamics of the financial system and is applicable across diverse economic scenarios (Bespalova, 2015; Handoyo et al., 2020; Gupta & Kumar, 2022). Table 13 presents out-of-sample model performance for each variable's optimal horizon and GSB/QPS values at the upper and lower thresholds. A shorter optimal time horizon suggests a rapid response to vulnerabilities when risk levels are high.

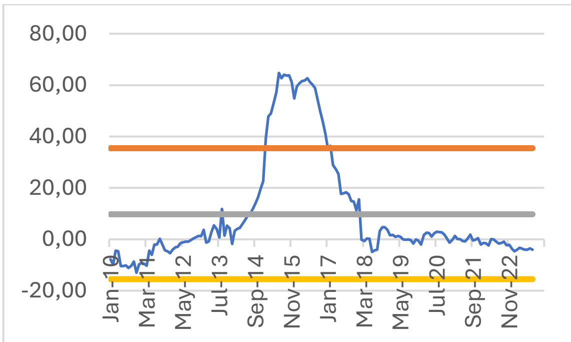
Table 13. Out-sample of Islamic Banking Performance

VARIABLE	TIME HORIZON	QPS	GSB	THRESHOLD
FDR	1 Month	0.8589	0.0067	Upper
	1 Month	0.9080	0.0301	Lower
NPF	1 Month	0.5890	0.0003	Upper
	3 Months	0.6135	0.0067	Lower
BS	1 Month	0.147	0.003	Upper
	6 Months	1.342	0.231	Lower
TPF	1 Month	0.8589	0.1020	Upper
	6 Months	0.684	0.060	Lower
CIB	12 Months	1.053	0.002	Upper
	3 Months	0.9882	0.0031	Lower

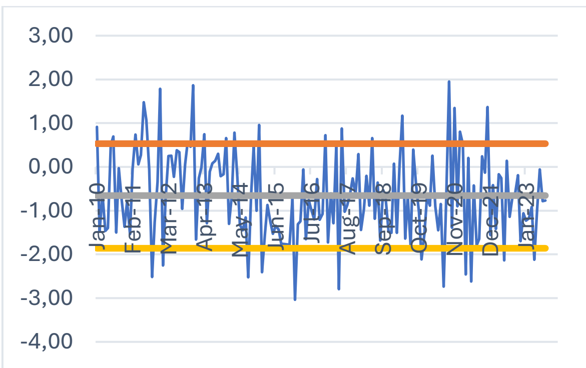
Figure 4 is a visualisation of the individual movements of the index variables relative to static thresholds in Islamic banking. The threshold values indicate that the performance of each variable and the period of its movement are at the optimal threshold (resilience) or exceed the lower or upper thresholds (vulnerable or stagnant). In the context of banking resilience, visualisation is essential as a surveillance tool for policymakers to monitor the development of each variable, mitigate the impact of risk, and prevent the probability of banking risk from increasing.



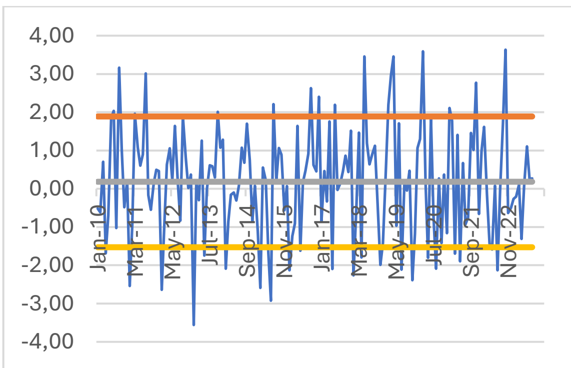
Optimal Level Index IFDR



Optimal Level Index INPF



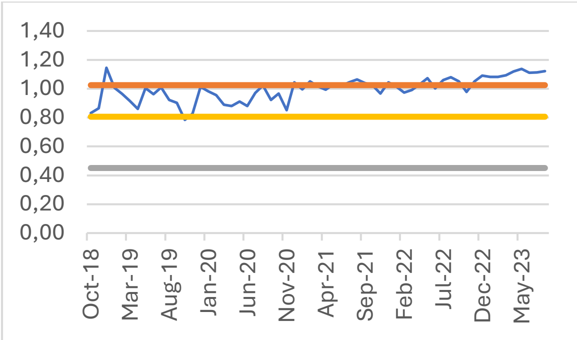
Optimal Level Index ITPF



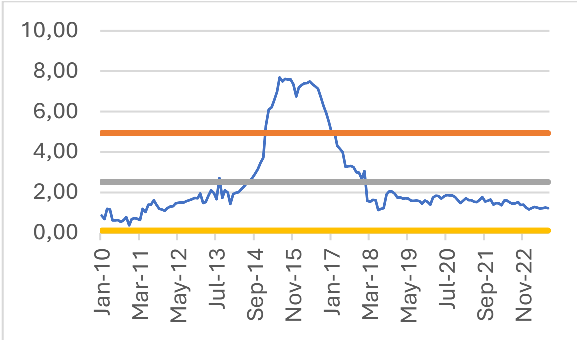
Optimal Level Index IBS

Figure 4. Optimal level in the Islamic Banking variable index.

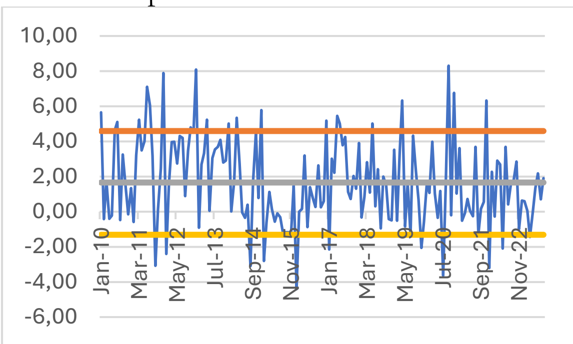
Figure 5 depicts the movement of individual variables in the form of their absolute values or actual values (in percentage). The results revealed that each variable fluctuated between optimal (between the ideal thresholds) and non-optimal (stagnant and vulnerable) positions. The optimal position depends on the variable's characteristics—whether "high is good" or "low is good"—and on the choice of scale.



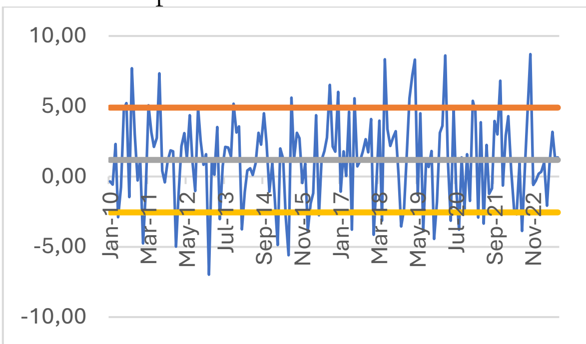
Optimal Level Index FDR



Optimal Level Index NPF



Optimal Level Index BS



Optimal Level Index TPF

Figure 5. Optimal level in real variables of Islamic banking

In the banking variables, Bank Size (BS), Third-Party Fund (TPF), and FDR variables are coded as "high is good," while only NPF is coded as "low is good." This categorisation affects the position labelled "optimal" in Figure 5. For the "high is good" variable, the optimal variable movement condition is between the middle and upper thresholds.

Table 14. Head map of Islamic Banking

Years	Month	FDR	NPF	BS	TPF	CIB
2010	Jan-10	141.30	0.86	5.66	-0.33	32.42
	Feb-10	141.36	0.67	-0.43	-0.57	31.35
	Mar-10	141.29	1.18	1.75	2.31	34.26
	Apr-10	141.36	1.15	-0.40	-2.89	34.04
	May-10	141.42	0.62	-0.23	-0.74	31.10
	Jun-10	141.37	0.61	4.63	4.82	31.15
	Jul-10	141.33	0.64	5.10	5.21	31.31
	Aug-10	141.31	0.54	-0.49	-1.46	30.51
	Sep-10	141.23	0.63	3.25	7.69	31.18
	Oct-10	141.24	0.78	1.42	3.02	31.93
	Nov-10	141.25	0.37	-0.16	-0.27	29.50
	Dec-10	141.22	0.68	1.34	1.23	31.30

Description: Red indicates variables in vulnerable conditions; Yellow indicates variables in the tolerance conditions; Green indicates variables in resilience conditions; Blue indicates variables in stagnant conditions.

Table 14 demonstrates the stages of the variable conditions per month during the observation period, illustrated by colour variations. In the context of individual variables, such as FDR, NPF, BS, and TPF, the head map shows the distribution of variable conditions at a given time. The head maps can identify areas with high intensity (vulnerable or stagnant) or low intensity (resilient or tolerant) in the data they represent.

This visualisation stage evaluated prior signalling thresholds and in-sample models using the signal-crisis matrix framework. The out-sample model results identified crisis signals based on the optimal time horizon that minimises the Quadratic Probability Score (QPS) for accuracy and the Global Square Bias (GSB) for calibration. Additionally, an optimal-level assessment determined each variable's status (optimal, tolerant, stagnant, or vulnerable) in Islamic banking, as shown in Table 15. The short-term horizons suggest that risks in the banking sector escalate quickly, necessitating prompt responses to limit potential losses and bolster resilience in NTB's Islamic banking. The significance of an optimal time horizon is that it helps policymakers strike a balance between preventive and mitigative measures in confronting Islamic banking vulnerability.

Table 15. Visualisation of Islamic Banking Variables

Variable	Optimal	Tolerance	Stagnant	Vulnerable	Time Horizon	QPS	GSB	Threshold
FDR (%)	81 ≤ FDR ≤ 102	45 ≤FDR<81	FDR <81	FDR>102	1 Month	0.85	0.01	Upper
					1 Month	0.90	0.03	Lower
NPF (%)	1.29 ≤ NPF ≤ 1.89	1.59 < NPF ≤ 1.89	NPF < 1.29	NPF > 1.89	1 Month	0.58	0.01	Upper
					3 Months	0.61	0.01	Lower
BS (%)	3.79 ≤ BS ≤ 4.59	2.98 ≤ BI < 4.59	BS <2.98	BS>4.59	1 Month	0.15	0.01	Upper
					6 Months	1.34	0.23	Lower
TPF (%)	4.16 ≤ TPF ≤ 4.58	3.73 ≤ TPF < 4.16	TPF < 3.73	TPF > 4.58	1 Month	0.86	0.10	Upper
					6 Months	0.68	0.06	Lower
CIB	10.66 ≤ CI ≤ 28.14	-6.61 ≤ CI < 10.66	CI < -6.61	CI > 28.14	12 Months	1.05	0.01	Upper
					3 Months	0.99	0.01	Lower

Table 16. Visualisation of research results threshold with the threshold of the government and the monetary authority (Monthly Percentage)

Variable	Government Provisions	Research Result	Condition
FDR* (Percentage)	78 ≤ FDR ≤ 92	81 ≤ FDR ≤ 102	Not yet appropriate (Overestimate)
NPF** (Percentage)	NPF ≤ 5	1.59 ≤ NPF ≤ 1.29	Appropriate
BS*** (Percentage)	3.64 ≤ BS ≤ 5.12	2.98 ≤ BS ≤ 4.59	Not yet appropriate (Underestimate)
TPF****	7.32 ≤ TPF ≤ 8.15	2.98 ≤ TPF ≤ 4.58	Not yet appropriate (Underestimate)

*FDR, based on Bank Indonesia provisions 2013; **NPF, based on Bank Indonesia provisions 2015; **INF, based on Regional Inflation assumptions and Bank Indonesia Provisions 2021; ***BS, based on Bank Indonesia provisions 2022; ****TPF, based on the assumptions of the Ministry of Finance of the NTB Regional Office 2023

In analysing Islamic banking resilience, calculated threshold conditions were categorised as underestimated, appropriate, or overestimated and compared with government and monetary authority standards for each variable. The FDR was overestimated, exceeding the ideal government range of 78% to 92% by, ranging from 81% to 102%, indicating a high liquidity risk due to an imbalance between financing and fund collection. The NPF was within an appropriate range, aligning with the government's maximum of 1.59% to 29%. This indicates that Islamic banking maintained sound financing quality at optimal levels. The Bank Size (BS) was underestimated, falling below the expected 3.64%-5.12% range, with a value between 2.98% and 4.59%. This suggests limited capacity to fully support economic growth. Similarly, the TPF was underestimated, increasing from 2.98% to 4.58%, below the target range of 7.32% to 8.15%. Islamic banking should be more innovative and attractive to attract a large number of depositors (Table 16).

Conclusion

The study of the resilience of Islamic banking in West Nusa Tenggara Province is essential, given the gradual expansion of its offices and assets. However, rising risks in banking operations can increase pressure, leading to banking vulnerability. Consequently, a prolonged period of imbalance can weaken banking resilience, as its balance sheets cannot absorb the escalating risks. The Early Warning System (EWS) approach, involving 15 integrated steps, helps monitor resilience by using variables of FDR, BS, NPF, and TPF against their optimal thresholds.

The results show that the optimal time horizon for these variables is mostly under one year (short term), highlighting the need for rapid policy responses to prevent systemic vulnerability and mitigate its impact. This brief time horizon underscores the urgency for prompt decision-making to maintain resilience. The findings also show that aligning resilience levels with regulatory thresholds is vital. Deviations—whether above or below targets—indicate excessive or cautious trends, suggesting the need for adjustments. Thus, resilience requires leading variables to assess risks, an optimal time horizon for policy action and reaction, and a defined threshold to guide monitoring and ensure stability. This study is significant for evaluating the degree of compliance by comparing stipulated and estimated thresholds. Islamic banking in NTB province can effectively control NPF, provided its movements remain within the specified thresholds. However, FDR, BS, and TFT need to be adjusted because they have exceeded regulatory thresholds. Therefore, this study is essential for monitoring operational aspects in the banking industry and would be a significant tool for addressing issues arising from escalating risks and a gradual decline in resilience.

Acknowledgement

The authors are grateful to the anonymous reviewers for their valuable comments and insights, which helped improve the quality of the paper.

Author contributions

Both authors contributed equally to the conception, design, analysis, and interpretation of the study, as well as to the drafting and revision of the manuscript. Both authors have read and approved the final version of the manuscript.

Use of AI tools declaration

The authors used AI tools (ChatGPT and DeepSeek) for language editing and grammar review of this manuscript. The authors are fully responsible for the content of this publication.

Conflict of interest

The authors declare no conflicts of interest.

References

Ahmad, S., Ahmad, W. M. W., & Shaharuddin, S. S. (2022). Is an excess of everything bad? Ramifications of excess liquidity on bank stability: Evidence from the dual banking system. *Borsa Istanbul Review*, 22, S92-S107. https://doi.org/10.1016/j.bir.2022.09.008

Albaity, M., Mallek, R. S., Bakather, A., & Al-Tamimi, H. A. H. (2023). Heterogeneity of the MENA region's bank stock returns: Does country risk matter?. *Journal of Open Innovation:*

Technology, Market, and Complexity, 9(2), 100057. https://doi.org/10.1016/j.joitmc.2023.100057

Azwar, P., & Tyers, R. (2015). Indonesian macro policy through two crises. *Journal of Southeast Asian Economies*, 37(2), 101-134. https://doi.org/10.2139/ssrn.2610963

Bank Indonesia. (2015). *Peraturan Bank Indonesia nomor 17/10/PBI/2015 tentang rasio loan to value atau rasio financing*. Jakarta: Bank Indonesia.

Berg, A., & Pattillo, C. (1999). Are currency crises predictable? A test. *IMF Staff papers*, 46(2), 107-138. https://doi.org/10.2307/3867664

Bespalova, O. (2015). The Good, the Bad, and the Ugly signals of currency crises: Does the signal approach work in ex-ante forecasting of currency crises?.

Caldera-Sánchez, A., de Serres, A., Gori, F., & Röhn, O. (2017). Strengthening economic resilience: Insights from the post-1970 record of severe recessions and financial crises. *OECD Economic Policy Paper*, 20, 1-29. https://doi.org/10.1787/6b748a4b-en

Domala, V., & Kim, T. W. (2023). Application of empirical mode decomposition and Hodrick-Prescott filter for the prediction of single-step and multistep significant wave height with LSTM. *Ocean Engineering*, 285,115229. https://doi.org/10.1016/j.oceaneng.2023.115229

Fitri, R. M., & Hafiz, S. G. (2022). Determinants analysis of Islamic and conventional banks' systemic risk potential: A preliminary study. *Studies in Business and Economics*, 17(1), 202-217. https://doi.org/10.2478/sbe-2022-0014

Fu, K., Xia, J. B., Zhang, X. Y., & Shen, J. (2017). System structural analysis of communication networks based on DEMATEL-ISM and entropy. *Journal of Central South University*, 24(7), 1594-1601. https://doi.org/10.1007/s11771-017-3564-z

Gabus, A., & Fontela, E. (1973). Perceptions of the world problem atique: Communication procedure, communicating with those bearing collective responsibility. DEMATEL Report No.1, Battelle Geneva Research Centre, Geneva.

Ghosh, R., Ahmed, T., & Khan, Z. I. (2020). Assessing the resilience of the banking system of Bangladesh: A micro stress testing approach. *European Journal of Applied Business and Management*, 6(2), 1-34. https://doi.org/10.58869/EJABM

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 37(3), 424-438. https://doi.org/10.2307/1912791

Gupta, N., & Kumar, A. (2022). Comparing parametric, semi-parametric and non-parametric early warning systems for banking crisis: Indian context. *Global Business and Economics Review*, *26*(2), 111-134.

Handoyo, R. D., Erlando, A., & Astutik, N. T. (2020). Analysis of the twin deficits hypothesis in Indonesia and its impact on the financial crisis. *Heliyon*, *6*(1).

Kaminsky, G. L., & Reinhart, C. M. (1999). The twin crises: The causes of banking and balance-of-payments problems. *American Economic Review*, 89(3), 473-500. https://doi.org/10.1257/aer.89.3.473

Kanas, A., Vasiliou, D., & Eriotis, N. (2012). Revisiting bank profitability: A semi-parametric approach. *Journal of International Financial Markets, Institutions and Money*, 22(4), 990-1005. https://doi.org/10.1016/j.intfin.2011.10.003

Khan, A., Chaudhry, I. S., & Saeed, S. (2019). Islamic VS conventional commercial banking: The resilience avant-garde. *Journal of Accounting and Finance in Emerging Economies*, 5(2), 261-274. https://doi.org/10.26710/jafee.v5i2.921

Maliha, H., & Marlina, L. (2019). Why are Islamic banks relatively more resilient to crises?. *Ekonomi Islam Indonesia*, 1(1), 34-55. https://doi.org/10.58968/eii.v1i1.3

Nugroho, M. R., Kurnia, A. S., Qoyum, A., & Fardila, F. (2020). The resilience of the Indonesian banking system and macroeconomic fluctuation: Islamic versus conventional banking. *Journal of Islamic Monetary Economics and Finance*, 6(2), 419-438. https://doi.org/10.21098/jimf.v6i2.1135

Özdemirci, F., Yüksel, S., Dinçer, H., & Eti, S. (2023). An assessment of alternative social banking systems using T-Spherical fuzzy TOP-DEMATEL approach. *Decision Analytics Journal*, *6*, 100184.

Pratama, S. D., & Rizal, R. (2019). The resilience of Islamic banks in facing the economic dynamics in Indonesia. *Journal of Accounting and Finance in Emerging Economies*, 5(2), 261-274. http://dx.doi.org/10.26710/jafee.v5i2.921

Ravn, M. O., & Uhlig, H. (2002). On adjusting the Hodrick-Prescott filter for the frequency of observations. *Review of Economics and Statistics*, 84(2), 371-376. https://doi.org/10.1162/003465302317411604

Saaty, T.L., (1990). How to make a decision: The analytic hierarchy process. *European Journal of Operational Research*, 48(1), 9-26. https://doi.org/10.1016/0377-2217(90)90057-I

Seker, S., & Zavadskas, E. K. (2017). Application of fuzzy DEMATEL method for analysing occupational risks on construction sites. *Sustainability*, 9(11), 2083. https://doi.org/10.3390/su9112083

Setyawati, I., Widyastuti, T., & Suryati, A. (2019, October). Sharia Bank Resilience in Facing Macroeconomic Factors. *2019 International Conference on Organizational Innovation (ICOI 2019)*, Indonesia, 15-20. https://doi.org/10.2991/icoi-19.2019.4

Setyawati, I., Karyatun, S., Awaludin, D. T., & Wiweka, K. (2022). Stability and resilience of the Islamic banking system: A closer look at the macroeconomic effects. *Calitatea*, 23(187), 295-304. https://doi.org/10.47750/QAS/23.187.36

Shakeri, H., Khalilzadeh, M., Raslanas, S., & Kazimieras Zavadskas, E. (2021). What do project managers need to know to succeed in face-to-face communication?. *Economic research-Ekonomska istraživanja*, 34(1), 1094-1120. https://doi.org/10.1080/1331677X.2020.1819851

Wiranatakusuma, D. B. (2018). Constructing the Islamic banking resilience index in Indonesia. *Journal of Islamic Monetary Economics and Finance*, 3, 45-62. https://doi.org/10.21098/jimf.v3i0.760