MEASURING RESILIENCE OF THE BANKING SECTOR IN MALAYSIA

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ABSTRACT

Financial crises followed shock and weakness in the financial system. The banking sector, which rules the financial sector in Malaysia and other regions, becomes influenced by banks' financial crises. This study, therefore, aims to investigate the resilience of the Malaysian banking sector to increased banking system vulnerabilities. The study utilized early warning systems. It constructs a composite index using four selected macroeconomic and financial ratio indicators for the aggregate banking sector from January 2011 to December 2023. The main key results suggest that adequate macroeconomic indicators and banking performance can be used to improve banking fundamentals. The Non-Performing Loan (NPL) change is estimated to be between 0.98% and 1.22%, the Loan Deposit Ratio (LDR) between 80.02% and 81.48 percent, the Capital Adequacy Ratio (CAR) between 14.75% and 16.21 percent, and the Return on Assets (ROA) from 1.40% to 1.52%. Furthermore, inflation (INF) should be 0.10 to 0.17 %; exchange rate (ER) should be 3.49 to 3.80 Malaysian Ringgit (MYR) per USD; GDP growth should be 1.39% to 1.91% and Stock Market Index (SMI) growth should be 0.03% to 0.39%.

Keywords: Banking sector, resilience, optimal level, macroeconomic indicators, extraction signal approach

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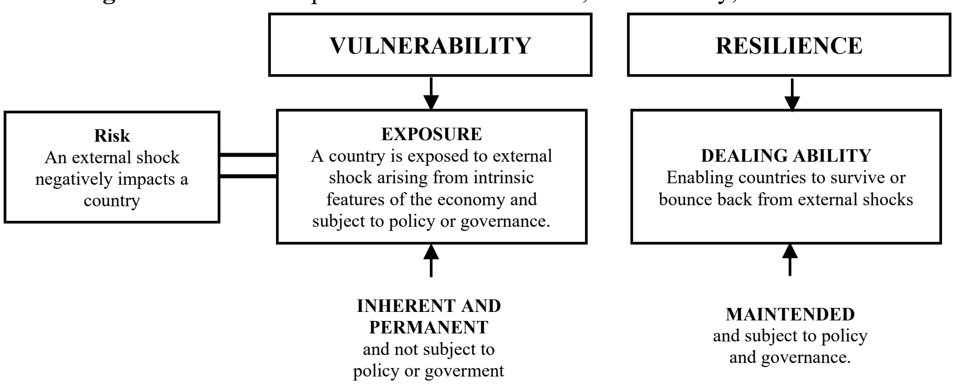
1. INTRODUCTION

The 2007–2008 crisis saw a sharp increase in global financial market volatility, which had a negative impact on banking systems all over the world. After Lehman Brothers and other large financial institutions failed, the linkage volatility index reached its peak. Asian economies and the global market had already been shook by the 1997–1998 Asian Financial Crisis. Financial system stability, according to Bilgin et al. (2021), is the capacity of banks to endure economic upheaval while continuing to be sound and functional. The macroeconomic environment has a big impact on the expansion of and profitability of banks (Athanasoglou et al., 2008; Brown et al., 2019; Asyiqin & Rinaldi, 2025; Hariyadi & Johari, 2025; Ichsan et al., 2024). Recessions, interest rate hikes, GDP growth, inflation (INF), and other factors can exacerbate stress, reduce resilience, and increase risk.

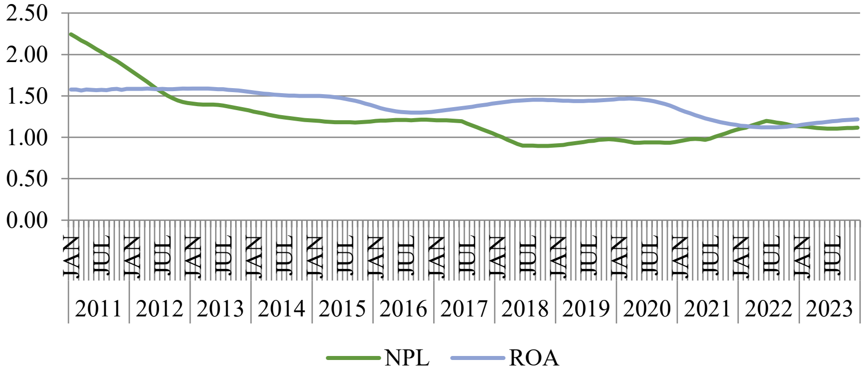
Figure 1: Relationship between external shock, vulnerability, and resilience



Source: Briguglio, (2009)

Figure 1 shows how GDP, inflation (INF), exchange rates (ER), and stock market indices (SMI) all work together to create external shocks, vulnerability, and resilience. Risk indicates a nation's susceptibility to macroeconomic fluctuations and its ability to withstand shocks. Policies that reduce vulnerability, keep inflation stable, control exchange rates, and make the domestic economy stronger are therefore very important (Briguglio, 2009). In Malaysia, the financial market was still based on banks in 2023, with banks holding 50.1% of all financial assets (Bank Negara Malaysia, 2024a). This kind of structure suggests that instability could spread throughout the system. Still, by the middle of 2023, the sector was stable even though things were unclear. COVID-19 raised the number of Non-Performing Loans (NPL) to 1.8%, which is still below the 5% limit (Surwanti & Wardana, 2024). The Capital Adequacy Ratio (CAR) of 16.2% showed that the company was capitalized, which was more than the Basel III requirement of 8% (Beck et al., 2021). Figures 2 and 3 show numbers related to banking.

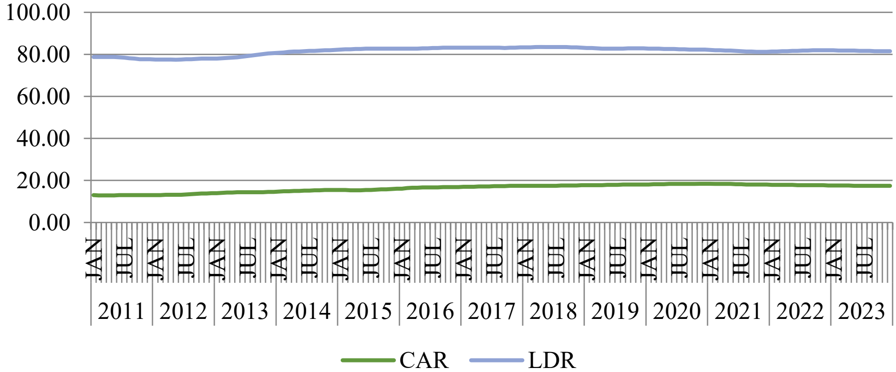
Figure 2: Summary statistic of variable NPL and ROA (in percentage)



Source: Developed by Authors

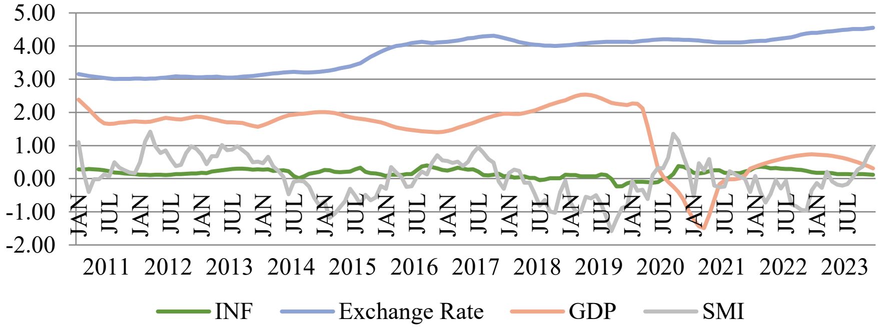
ROA is 1.2%, which banks still earn money and keep growing money (Iqbal et al., 2021; Johari, 2024; Afandi et al., 2024). The Loan-to-Deposit Ratio (LDR) keeps lending and deposit inflows balanced at about 89%, so that liquidity and credit keep growing (Abou-El-Sood, 2022). There are strong rules and good risk management (Al Rahahleh et al., 2019; Majid et al., 2025., Wiranakusuma et al., 2025) that helped ensure the industry still has strength, however, financial instability outside of the region (worldwide) needs to be actively monitored. The relationship between banking performance and the activities of the businesses and consumers in the overall economy is very interrelated (Lietaer, 2017; Pratiwi et al., 2023). Economic growth also depends on financial development, which, when conducted too much, can be susceptible to vulnerabilities (Loayza et al., 2018). Results from Qatar point to a positive bidirectional relationship between financial deepening and growth and economic disruption to non-oil GDP can upset both (Alsamara et al., 2018)

Figure 3: Summary statistic of variable LDR and CAR (in percentage)



Source: Developed by Authors

Figure 4: Summary statistic of the economy in Malaysia (in percentage)



Source: Developed by Authors

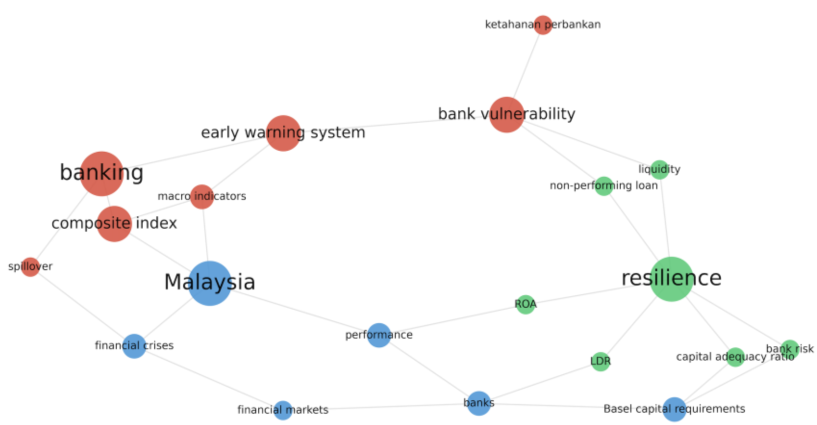
Figure 4 shows the trends of most important macroeconomic variables (INF, ER, GDP, SMI) in 2011–Mid-2023. Pandemic-induced inflation rate spiked during 2020-2021 and stabilized by 2022-2023. The exchange rate depreciated notably between 2014 and 2019; by 2020 and 2023 has stabilized slightly. GDP remained steady until a sharp decrease within the range of 2020-2021 with relatively slight recoveries; the SMI was volatile in 2011-2013, stable in the span of 2014-2019 and high volatility in 2020-2021 until recovery in 2022-2023. Other studies show similar NPL ratios have been found in the banking industry but LDR, ROA and CAR have been significantly more divergent than these two standards.

Data Envelopment Analysis (DEA) reveals that Malaysian banks achieve optimal efficiency. In the same vein, Widodo (2021) further stresses the significance of CAR, LDR, ROA, and NPF in shaping banks' financial performance in Malaysia. The resilience indicators indicate that a study on resilience in the banking sector is importance for this country as it affects the stability of the financial sector. Moreover, resilience is essential to sustainable economic growth. Thus, the research study endeavors to design optimal levels for banking resilience to withstand economic uncertainties. It recognizes macroeconomic indicators affecting Malaysian banks, assesses the resilience of banking indicators, and establishes a balanced assessment framework.

2. LITERATURE REVIEW AND RESEARCH FRAMEWORK

Kaminsky and Reinhart (1996) point out that in the face of economic turmoil a quick response of banks to internal risks is a necessity. Delays can cause banks to fail, instill public distrust in the institution, lead to bank runs, or a recession. This instability decreases banking service consumption, non-interest income, and profitability (Beck & Keil, 2021). Sustainable banking needs so much more than access to capital but also governance capacity, liquidity, and flexibility (Cecchetti & Tucker, 2016). The Early Warning System (EWS) seeks out macroeconomic crisis signs and supports proactive efforts to prevent risk through early warning (Kusuma & Duasa, 2016; Mawardi et al., 2023). Given that there are higher sectoral risks (Rahman & Shahimi, 2010), this study uses VOSviewer to map resilience themes. It identifies 17 frequently occurring important keywords in the literature and their connections (and interrelationships) with each other.

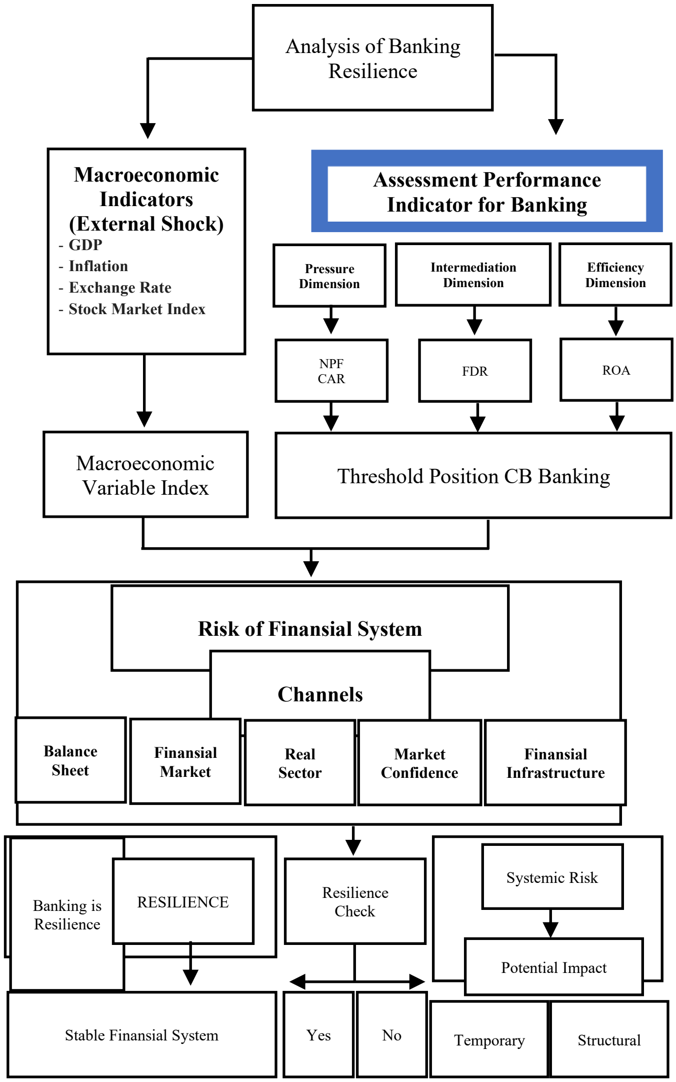
Figure 5: Visualization of keywords with a minimum occurrence of 4



Source: Developed by Authors (Vosviewer)

Figure 5 shows a network diagram of keywords related to banking resilience. While "resilience" and "banking" are the major nodes, the clustering doesn't fit perfectly with the Basel regulatory framework where NPL, CAR, and ROA are used as financial soundness indicators. The diagram, however, focuses on more general terms such as "bank risk" and "performance," which do not fully describe these measures. The absence of key macroeconomic variables, which are necessary for evaluating resilience, limits the network's ability to elucidate the interplay between internal banking conditions and overarching economic dynamics. Figure 6 shows the research framework, which connects asset growth, financing activities, third-party fund mobilization, and Malaysian banking structures. It is expected that regulatory expansion will help the sector grow in a sustainable way.

Figure 6: Research framework



Source: Wiranatakusuma (2018), Modified by Authors

Figure 6 presents macroeconomic measures such as GDP, inflation, exchange rates, and stock market indices as external shocks and demonstrates the capacity of banks to manage financial risks. Non-Performing Loans (NPL), Capital Adequacy Ratio (CAR), Financing/Loan to Deposit Ratio (FDR/LDR), as well as Return on Assets (ROA) measure the banking industry health. These represent pressure, intermediation, and efficiency. In financial stability analysis, pressure indicates systemic stress, intermediation evaluates fund allocation effectiveness, and efficiency means whether banks can generate returns through prudent management of funds (Borio & Drehmann, 2009; Čihák & Schaeck, 2010).

Banks resilience is evident from their balance sheets, financial markets, the real sector, market confidence (Fatmawati et al., 2024), and financial infrastructure with a stability of the financial system reflecting strength and weaknesses indicating systemic vulnerability. Using a composite index of NPL, CAR, LDR and ROA primary risk indicators on the bank side and macroeconomic variables such as inflation, GDP growth, exchange rates and stock market indices, this research uses this EWS and signal extraction approach to measure resilience. However, broader channels of resilience such as real sector capacity, market confidence, financial infrastructure are largely unmet owing to limited data and measurable means (Wiranatakusuma, 2018). The allocation of credit in productive and speculative sectors will indirectly yield real sector exposure by reflecting where very high non-productive asset risk and cyclical risk, is higher risk, by the rise of cyclical risk (Pratama & Darmawan, 2023; Huda & Santosa, 2022). Credit default swap spreads, interbank rates and confidence indices may be relevant for future investigations (Beck et al., 2021; Cecchetti & Tucker, 2016). Financial infrastructure resilience is also dependent on liquidity, payment systems and regulation of systems too (BNM, 2024; BIS, 2009). Ongoing resilience demands even balanced asset quality and capitalization — not just between intermediation and profitability. Thus, on the basis of the literature and research framework, banks' resilience is measured in financial indicators (NPL, CAR, LDR, ROA) and macroeconomic shocks (GDP, inflation, exchange rates, stock markets). Resilience includes more than capital; it also includes the quality of intermediation, the profitability of the institution in terms of its business, governance structure and adaptability, whereas balanced assets, responsible funding and solid infrastructure sustain the stability through economic uncertainty.

3. RESEARCH METHODOLOGY

3.1 Type of Data

The data used in this research are secondary, monthly time-series data covering the period from January 2011 to December 2023.

3.2 Data Sources

In this research, the author collected secondary data through documentation and literature reviews from various domestic institutions. The institutions that are the primary sources of secondary data in this research, as reported in table 1, include Bank Negara Malaysia and the Department of Statistics Malaysia.

Table 1: Data sources

Variable and Form	Explanation	Source
Gross Domestic Product (GDP) Growth (in percentage)	Gross domestic product by expenditure in constant prices	Department of Statistics Malaysia, 2024c
Inflation (in percentage)	Inflation rate based on Consumer Price Index (CPI), monthly data 2011-2023	Department of Statistics Malaysia, 2024a
Exchange Rate (absolute value)	The nominal exchange rate of the Malaysian Ringgit (MYR) compared to the USD	Department of Statistics Malaysia, 2024b
Malaysia Stock Market Index (in percentage)	Monthly history of the Malaysia Stock Market Index	FTSE Bursa Malaysia KLCI (Yahoo Finance, 2024)
4 Variables of Banking Financial Ratios (in percentage)	Financial Ratio of Commercial Banks	Bank Negara Malaysia (2024b)

3.3 Steps for Constructing a Composite Indicator on the Banking Resilience Index

This study creates a composite Bank Resilience Index (table 2) by using exogenous scaling based on Nardo's (2005) indexation method, which Nguyen et al. (2020) changed. The framework adheres to a methodical procedure of theory identification, indicator selection, weighting, normalization, and validation. It is possible to look at how banks do over time by separating endogenous and exogenous variables. Endogenous indicators—like ROA, CAR, LDR, and NPL—show how internal factors like risk exposure, management quality, and operational decisions affect each other, showing that risk, profitability, and capital are all related in the opposite way. Exogenous factors, such as GDP growth, inflation, interest rates, and regulatory frameworks, affect banking conditions from the outside, but bank performance does not directly affect them (Barth et al., 2004).

Table 2: Constructing the banking resilience index and macroeconomic indicators for resilience

	Steps
1.	Building a Theoretical framework: The first step provides the basis for selecting and combining variables into a meaningful composite index under a fitness-for-purpose principle.
2.	Transforming data into the index: This step should be carried out to render the variables comparable. $I_{it} = \frac{(X_{it} - \bar{X}_i)}{\sigma_i}$ I_{it} = *The single index value of variable I at time t* X_{It} = *The value of a variable I at time t* $\overline{X}_I$ = *The average value of variable I at time t* σ_I = *Standard deviation of variable i*
3.	Selecting data and determining the base year: This step should be based on the analytical soundness, measurability, country coverage, and relevance of the indicators for the phenomenon being measured, as well as their relationships to each other (Wiranatakusuma, 2018). $S = \sqrt{\frac{1}{N-1}} \sum_{i=1}^{N} (X_t - \bar{X})^2$ S = Standard deviation X_t = The value of each observation in the sample ¯X = Sample mean in base year N = Number of observations in the sample
4.	Determining Weight: This step is the importance of a particular variable contributing to the bank's resilience. $Weighted\ Index_{ij} = \frac{Average\ of\ Variance_{ij}}{Total\ Variance}$ Determining the weight of each variable in this study significantly impacts the overall composite indicator. In this paper, we employ a model weighting approach to calculate the extent of variation in each year's variables relative to the total variation in a single composite index. Variance is a statistical measure of how far each data point in a set is from the mean (average) and from every other data point (monthly data). It identifies the extent of the spread or dispersion of data on an annual basis during the period of observation.
5.	Index Aggregation: This step should be taken according to the underlying theoretical framework. • $MCI_t = w * IGDP_t + w * IINF_t + w * IER_t + w * ISMI_t$ • $BCI_t = w * INPF_t + w * ICAR_t + w * ILDR_t + w * IROA_t$ IGDP, IINF, IER, ISMI = Index GDP, Index inflation, Index Exchange Rate, and Index Stock Market INPF, ICAR, ILDR, IROA = Index NPF, Index CAR, Index LDR, Index ROA

	Steps
	X_t = The value of each observation $\bar{X}$ = Sample mean in base year N = Number of observations in the sample BCI = Banking Composite Index MCI = Macroeconomic Composite Index, t = time period
6.	Utilizing Factor Analysis: This step should be undertaken to assess the composite index's consistency. The recommended HCR value is not more than 0.10 or 10% (Saaty, 2008).
7.	Setting Threshold: This step sets the recommended threshold for measuring the index's performance (Fontela & Gabus, 1976; Tzeng et al., 2007; Wiranatkusuma, 2018). $\alpha = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}[t_{ij}]}{N} R_i = \left[\sum_{j=1}^{n} t_{ij}\right]_{n*1} = [t_i]_{n*1}$ *α = Threshold value* *R_i = Rows in matrix T* *C_j = Columns in the matrix T* *I = DEMATEL Scale Line* *J = DEMATEL Scale Column* DEMATEL (Decision-Making Trial and Evaluation Laboratory) is a Multi-Criteria Decision-Making (MCDM) analytical method used to determine cause-and-effect relationships in complex systems. Decision-makers can characterize significant factors as either cause or effect, measure factor interactions, and construct cause-and-effect diagrams based on this strategy. DEMATEL defines variables, constructs a direct relationship matrix, calculates direct and total relationship matrices, and classifies factors into cause-and-effect groups (Fontela & Gabus, 1976; Tzeng et al., 2007). In this way, DEMATEL is able to examine multidimensional and complex system issues such as public policy, banking resilience, sustainability, risk management, and technological systems.
8.	Signaling Threshold: This indicates the individual index's performance compared to the estimated thresholds. This signaling threshold is a part of the Early Warning System methodology, which is effective for identifying impending economic turbulence. This phase facilitates prompt threat identification, issues alerts, and enables swift preventive or mitigation measures. Codes 0 and 1 are assigned for variables within a specific month, using the pre-specified multiplier threshold (Wiranatakusuma, 2018), to set the signaling threshold.
9.	Estimating In-sample model: This step is to build the most appropriate model to measure the bank's. The in-sample model used in this study was employed to estimate the long-term trajectory of a company's operational resilience cycle. A prevalent method for detecting this cycle is the Hodrick-Prescott (HP) Filter. The HP Filter method isolates cyclical components by resolving the optimization equation of a loss function (Wiranatakusuma, 2018).
10.	Estimating Out-of-sample model: This step assesses the model's ability to explain the performance of the variables. The Out Sample Model employs a crisis-signal matrix framework, or an early warning system model, to assess prior signaling stages. Within the crisis-signal matrix framework, A represents the duration in months during which the indicator generates a positive signal, B denotes the duration in months when the indicator yields a negative signal due to erroneous signaling, C indicates the duration in months when the indicator neglects to issue a warning signal, and D signifies the duration in months when

Steps
the indicator remains inactive and no crisis occurs. The model is anticipated to elucidate or delineate the state or efficacy of each variable (Wiranatakusuma, 2018).
11. Out-Sample Model Performance: This step is to resume the performance of all variables used by using an out-of-sample model
12. Defining the optimal value in index form: This step defines the optimal value in index form. This stage is conducted to determine the variable index value at the most advantageous time horizon, regardless of whether the system is in an ideal, tolerant, stagnant, or vulnerable state. The ideal state is an optimal condition in which the variable's performance exceeds the average. The determination of this index value is significantly affected by the attributes of each variable. Certain variables exhibit "High is good" traits, whereas others display "Low is good" attributes (Wiranatakusuma, 2018).
13. Calculating the optimal value in the absolute form: This step shows the absolute value and thresholds.
14. Setting the heatmap: This step is needed to reveal the main drivers for an overall good or bad performance
15. Visualization of the results: This step should receive proper attention, given that the visualization can influence (help to enhance) interpretability

Source. Authors with modification

Table 3: The assessment of true and false signals of stress episode using a matrix crisis-signal framework

Items	Stress occurs in the next n months (C=1) (Pre-stress periods)	No stress occurs in the next n months (C=0) (Normal periods)
Signal (S=1)	**A** (Number of accurate imbalance signals)	**B** (Number of false imbalance signals, type 2 error)
No Signal (S=0)	**C** (Number of false balance signals-Type 1 error)	**D** (Number of accurate balance signals)

Source: Kaminsky & Reinhart (1996)

Table 3 shows the assessment of true and false signals of stress episodes using a matrix crisis-signal framework (Kaminsky, 1999)

The reasonable probability forecast for an event will be obtained when the optimal thresholds can be determined by minimizing the expected loss function and the sum of “anticipating errors” and “mitigating errors” with weights associated with each type of error, as shown in the equation below (Kaminsky, 1999; Wiranatakusuma,2018)

$$L(\mu,\tau) = \mu P T_{1(t)} + (1-P) T_{2(t)}$$

Where:

$L(\mu,\tau)$ = Lost Function

μ = Preference Parameter (The values are equal to 0,5)

τ = Threshold multiplier

P = The ratio P ($\frac{A+C}{A+B+C+D}$)

$T_{1(t)}$ = The number of values in the sample ($T_{1(t)} = \frac{C}{A+C}$)

$T_{2(t)}$ = The number of values in the sample ($T_{2(t)} = \frac{B}{B+D}$)

Evaluate probability estimates based on a comparison of estimated models with observable events. In practice, quadratic probability scores (QPS) are used as general assessment rules. Based on the research of Kaminsky (1999), QPS and GSB are used for each indicator of fragility and the construction of banking probability estimates and currency crises. The QPS has T probability forecasts:

$$QPS = \frac{1}{T}\sum_{t=1}^{T} 2\,(P_{T+t} - R_{T+t})^{\,t}$$

Note: *The QPS ranges from 0 to 2, with a score corresponding to perfect accuracy*

Where:

T = number of periods of observation

P_t = probability ($C_{t,\ t+n}$) of a crisis in the period (t, t+*n* months)

R_t = The actual time series of observations on ($C_{t,\ t+n}$) where $R_t = 1$

The forecast calibration is measured by the calibration of the global square bias (GSB) by comparing the probability of the average estimate with the observed relative frequency:

GSB = 2 ($\bar{P} - \bar{R})^2$

Note: *The GSB ranges from 0 to 2, with GSB = 0 corresponding to perfect global calibration, i.e., when the average probability estimate equals the average realization.*

Where:

$\bar{P} = \frac{1}{T}\sum_{t=1}^{T} P_t$

$\bar{R} = \frac{1}{T}\sum_{t=1}^{T} R_t$

T = number of periods of observation

P_t = probability ($C_{t,\ t+n}$) of a crisis in the period (t, t+n months)

R_t = The actual time series of observations on ($C_{t,\ t+n}$) where $R_t = 1$

Table 4: Developing the framework for resilience (integration process)

Steps
1. Building a Theoretical framework: The first step provides the basis for selecting and combining variables into a meaningful composite index under a fitness-for-purpose principle.
2. Setting the composite index: This step should be done as part of the underlying theoretical framework
3. Signaling Threshold: This step identifies the performance of an individual index relative to the estimated thresholds.
4. Performance Evaluation: This step is to evaluate the performance of all variables by using an out-of-sample model
5. Visualization of the results: This step should receive proper attention, given that the visualization can influence (help to enhance) interpretability

Source. Authors with modification

According to the previous reasoning, only the appropriate pressure index threshold can measure data quality. This research aggregates all specified factors using a pressure index. Four criteria determine the ideal time horizon: the lowest loss function, QPS, GSB, and signal horizon. Banking performance, an internal factor, and leading macroeconomic indicators, an external factor, must be integrated. Table 4 shows the five steps needed to assess Malaysia's banking sector's resilience.

4. RESULT AND DISCUSSION

The section will be divided into three parts: the visualization of the banking resilience index, the visualization of macroeconomic indicators for resilience, and the visualization of the banking resilience framework.

4.1 *Visualization Banking Resilience Index*

Table 5 shows the banking resilience index. A color-coded heat map (Table 6) is used to manually normalize shock intensity across indicators. This table shows the results of macroeconomic indexes. Green means the best conditions, yellow means the conditions are okay but could be better, blue means the conditions are getting tighter and could cause stagnation, and red means there are serious shocks that need to be dealt with right away. The heat map shows how four important index variables have changed over 156 months. Table 7 shows the overall results of banking resilience.

Table 5: Visualization of banking resilience index

<table>
<tr><th>Summary of Finding</th><th>Result and Discussion</th></tr>
<tr><td>1.</td><td>Dividing the banking shock dimension into three, namely the pressure dimension with NPL and CAR, then the intermediation dimension with LDR, and finally, the efficiency dimension with ROA as the indicator</td></tr>
<tr><td>2.</td><td>NPF's smallest standard deviation was 0.005. For the CAR, the smallest standard deviation was 0.079. Meanwhile, the LDR's smallest standard deviation is 0.057. Finally, the ROA's smallest standard deviation is 0.003.</td></tr>
<tr><td>3.</td><td>The non-performing loans (INPL) variable showed the lowest standard deviation in 2016. The capital adequacy ratio (ICAR) shows the lowest deviation in 2023. The Loan to Deposit Ratio (ILDR) reached its lowest deviation in 2017. Return on Assets (IROA) recorded the lowest deviation in 2012.</td></tr>
<tr><td>4.</td><td>The pressure dimension accounts for 56.34%, with NPL playing a dominant role. The intermediation dimension has an LDR of 1.70%, making it an important variable. Meanwhile, in the efficiency dimension, the ROA variable contributes 29.34%.</td></tr>
<tr><td>5.</td><td>$BCI_t = 0,563 * INPF_t + 0,017 * ICAR_t + 0,126 * ILDR_t + 0,293 * IROA_t$</td></tr>
<tr><td>6.</td><td>Coherence between variables is measured using the Analytical Hierarchy Process to obtain the Hierarchy Consistency Ratio (HCR), and the value is -0,084</td></tr>
<tr><td>7.</td><td>A series of steps is performed, and the multiplier threshold is set to the average of all variables in the T matrix. The average alpha threshold is 0.79.
<table>
<tr><th>T-Matrix</th><th>INPL</th><th>ICAR</th><th>IROA</th><th>IFDR</th></tr>
<tr><td>INPL</td><td>0,60</td><td>0,35</td><td>1,11</td><td>1,11</td></tr>
<tr><td>ICAR</td><td>0,95</td><td>0,32</td><td>1,30</td><td>1,30</td></tr>
<tr><td>IROA</td><td>0,55</td><td>0,28</td><td>0,62</td><td>0,89</td></tr>
<tr><td>IFDR</td><td>0,87</td><td>0,35</td><td>1,11</td><td>0,85</td></tr>
<tr><td colspan="4">Threshold value</td><td>0,79</td></tr>
</table>
Source: Authors' Calculation</td></tr>
<tr><td>8.</td><td>This process begins by assigning codes 0 and 1 to variables for a given month based on the calculated threshold multiplier. The threshold used is 0.79. If the index value exceeds 0.79, this indicates a state of banking turbulence in that period</td></tr>
<tr><td>9.</td><td>One widely used approach for identifying cycles in calculating long-term trends is the Hodrick-Prescott (HP) Filter. The HP Filter method separates the cycle components by solving the optimization equation of the loss function. The function λ is a smoothing parameter. This study used λ = 14400 as a smoothing parameter because the data have a monthly frequency. Next, the trend data will be coded as 1 and 0 as in the previous step.</td></tr>
<tr><td>10.</td><td>The process in the out-sample model step, between forecast and realization, or between signals and shocks, uses the Early Warning System (EWS) method to detect the emergence of combinations of shocks and vulnerabilities that can cause failure.</td></tr>
<tr><td>11.</td><td>The loss function, the smallest QPS, and the smallest GSB determine the optimal time horizon. The calculation results are the lowest QPS and GSB, most of which are within 3 months.</td></tr>
</table>

12.	This step is the final phase of modeling before conversion back to the original data. Four categories can be identified in the movement of banking indicators: expected (optimal) performance, tolerance, stagnation, and vulnerability.
13.	Ideally, NPL movements should range from 1,22% to 0,98% monthly. CAR movements should range from 16,21% to 14,75% monthly, LDR movements should range from 81,48% to 80,02% monthly, ROA movements should range from 1,40% to 1,52% monthly
14.	This study uses a heat map to visually represent the shock intensity of each indicator, with green indicating optimal conditions, yellow representing a tolerable state with room for improvement, blue indicating a stringent state that could lead to stagnation, and red indicating a shock that requires immediate intervention.
15.	To identify a coherent set of presentational tools for the targeted audience. To select the visualization technique that communicates the most information. To present the composite index results in a clear and accurate manner

Table 6: Visualization of heat map (number of months)

Summary	NPF	CAR	FDR	ROA
Vulnerable	21	48	33	40
Stagnant	39	37	33	33
Optimal	69	23	17	24
Tolerance	23	70	71	53

Source: Authors' Calculation

Table 7: Summary of banking resilience index

No	Indicator	Threshold	Optimal	Tolerance	Stagnant	Vulnerable
Lamdha=14400, Level of Multiplier 0,79						
Elements of Composite Index						
1A	CI	Upper	$-20{,}57 \leq CI \leq 13{,}15$	$-20{,}57 > CI \geq -54{,}30$	$CI < -54{,}30$	$CI > -20{,}57$
1A	CI	Lower				
2A	NPF	Upper	$1{,}22 \geq NPL \geq 0{,}98$	$1{,}22 < NPL \leq 1{,}46$	$NPL < 0{,}98$	$NPL > 1{,}46$
2A	(%)	Lower				
3A	CAR	Upper	$16{,}21 \geq CAR \geq 14{,}75$	$16{,}21 < CAR \leq 17{,}67$	$CAR < 14{,}75$	$CAR > 17{,}67$
3A	(%)	Lower				
4A	FDR	Upper	$81{,}48 \geq LDR \geq 80{,}02$	$81{,}48 < LDR \leq 82{,}93$	$LDR < 80{,}02$	$LDR > 82{,}93$
4A	(%)	Lower				
5A	ROA	Upper	$1{,}40 \leq ROA \leq 1{,}52$	$1{,}40 > ROA \geq 1{,}29$	$ROA < 1{,}29$	$ROA > 1{,}52$
5A	(%)	Lower				

Source. The author's calculation

Figure 7 illustrates that financial stability risks escalate as Non-Performing Loans (NPL) near the 5% threshold, especially during crises when NPLs exacerbate liquidity and solvency pressures (Nkusu, 2020). Levels below 5% usually help with stability and recovery, and levels around 2% are thought to be best for reducing long-term risk (Anastasiou et al., 2019; Kamarudin et al., 2021). This study shows that NPL ratios between 0.98% and 1.22% mean that banking is stable. Ratios above 1.46% mean that new risks are coming up and that regulators or managers need to step in.

The Capital Adequacy Ratio (CAR) is one of the important predictors of resilience. The resilience is increased by ratios more than 8%, and crisis management and market confidence by levels over 12% (Beck et al., 2021). If the CAR falls below 8%, people become less trusting and default risk increases. Nowhere is this more true than when below 6% (Iqbal et al., 2021). Banks with insufficient capital resources, in addition to losing money at an alarming rate, are more likely to do so during hardship (Abou-El-Sood, 2022). This study finds that banks' best CAR is concentrated between around 14.75% and 16.21%, which leaves them with the ability to manage shocks but still to expand. Banks' performance will be affected by the loan-to-deposit ratio (LDR). Close to 90% would increase the liquidity risk in times of instability (Ghenimi et al., 2021), whereas below 70% might imply a caution in lending and slow down the recovery of the economy (Shehzad et al., 2020). Indeed the optimal LDR range as a mix of income generation and liquidity is a combination between 80.02% and 81.48% based on this analysis. However, the risk of withdrawal increases if the ratio is greater than 82.93%. If the ratio is low, the deposits are not optimally utilized. Another measure of profitability is ROA. While above 1.52% is considered to help to enhance a company's resilience in a crisis (Ozili, 2021), values below 1% indicates that it is more prone for default (Ghenimi et al., 2021). Balanced ROA of 1.40%–1.52% assists with both stability and performance (Pham & Tran, 2020).

4.2 Visualization Macroeconomic Indicators for Resilience

Macroeconomic data that shows the resilience of something is shown in Table 8. A color-coded heat map (Table 9) details the full pattern of the macroeconomic index, with the overall results normalized for each indicator by shock intensity. Green means the best or expected conditions, yellow means conditions that are acceptable but could be better, blue means conditions that are getting worse and could lead to stagnation, and red means shocks that need to be dealt with right away. The heat map covers 4 macroeconomic-index variables over 156 months. Table 10 shows the overall resilience results based on these macroeconomic measures.

Table 8: Visualization of macroeconomic indicators for resilience

Summary of Findings	Purpose
1.	In summary, macroeconomic indicators serve as external shocks for the banking sector, including GDP (reflecting economic conditions), inflation (impacting purchasing power), exchange rates (affecting trade), and stock prices (influencing banks' capital-raising).
2.	The lowest standard deviation is 0.019 for inflation (INF). The exchange rate (ER) had the lowest standard deviation of 0.019. The GDP lowest standard deviation is 0.054. The stock market index (SMI) has the lowest standard deviation of 0.188.
3.	For inflation (INF), 2011 was the year with the lowest standard deviation. The standard deviation for the exchange rate (EXR) was lowest in 2012.

Summary of Findings	Purpose
	2011 was the year that saw the most stable economic growth (GDP). In the meantime, the stock market index (SMI) reached its lowest level in 2012.
4.	IGDP significantly affects the banking sector's resilience, underscoring the need to consider its impact on Malaysia's banking stability.
5.	$MCI_t = 0{,}234 * IINF_t + 0{,}161 * IER_t + 0{,}600 * IGDP_t + 0{,}002 * ISMI_t$
6.	Between-variable measurement is performed using the Analytical Hierarchy Process to obtain the Hierarchy Consistency Ratio (HCR). And the value is 0,0438
7.	The threshold multiplier represents an average across all variables in the T matrix, which gives an average alpha (threshold) of 0.59 for key macroeconomic indicators..
8.	It gives 0.59 as the threshold value which is based on the alpha value calculated in the previous step. If the index exceeds this multiplier, this indicates fluctuations in macroeconomic conditions.
9.	The Hodrick-Prescott (HP) Filter, used for the identification of cycles in long-term trend analysis, is a common method to decompose cycles by minimizing a loss function. So in this case, a smoothing parameter $\lambda = 14400$ is applied to monthly data. Following the previous steps to code the trend data as 1 and 0.
10.	For the out-sample model, the Early Warning System (EWS) is used to analyse the gap between forecasts and realizations (signals and shocks), to identify combinations of shocks and vulnerabilities that may lead to failure.
11.	The optimal time horizon is identified by the loss function, the smallest QPS, and the smallest GSB. The calculation results are the lowest QPS and GSB, most of which are within 3 months
12. .	In the final modeling phase before conversion to original data, four categories of banking indicator movements are identified: optimal performance, tolerance, stagnation, and vulnerability.
13.	Ideally, INF movements should range from 0,10% to 0,17% monthly. Exchange Rate movements should range from 3,49 to 3,80 monthly, GDP movements should range from 1,39% to 1,91% monthly, and SMI movements should range from 0,03% to 0,39% monthly.
14.	The heat map in this study visualizes shock intensity for each indicator using four colors: green for optimal conditions, yellow for tolerable states with improvement potential, blue for conditions at risk of stagnation, and red for shocks requiring immediate action.
15.	To identify a coherent set of presentational tools for the targeted audience. To select the visualization technique that communicates the most information. To present the composite index results clearly and accurately.

Table 9: Visualization of heat map (number of months)

Summary	INF	GDP	ER	SMI
Vulnerable	66	48	84	47
Stagnant	32	42	55	45
Optimal	50	1	5	30
Tolerance	21	68	21	34

Source: Authors' Calculation

Table 10: Visualization of macroeconomic indicators for resilience

No	Indicator	Threshold	Optimal	Tolerance	Stagnant	Vulnerable
Lamdha=14400, Level of Multiplier 0,59						
Elements of Composite Index						
1A	CI	Upper	2,12 ≤ CI ≤ 7,05	2,12 > CI ≥ -2,80	CI < -2,80	CI > 2,12
1A	CI	Lower				
2A	INF (%)	Upper	0,17≥INF≥0,10	0,17<INF≤0,24	INF < 0,10	INF > 0,24
2A		Lower				
3A	ER	Upper	3,80 ≥ ER ≥ 3,49	3,80 < ER ≤ 4,10	ER < 3,49	ER > 4,10
3A		Lower				
4A	GDP (%)	Upper	1,39 ≤ GDP ≤ 1,91	1,39 > GDP ≥ 0,87	GDP>1,91	GDP<0,87
4A		Lower				
5A	SMI (%)	Upper	0,03 ≤ SMI ≤ 0,39	0,03 > SMI ≥ -0,33	SMI>0,39	SMI<-0,33
5A		Lower				

Source. The author's calculation

Inflation of 0.10 percent to 0.17 percent per month helps stabilize the economy, as can be seen in table 10. If inflation is more than 5%, it increases borrowing cost and reduces the ability of people to purchase things (Cukierman et al., 2020). On a monthly basis, rates exceeding 0.24% might be more costly for vulnerable segments of the population. Conversely, inflation below 0.10% can lower consumption, investment, loan demand, and bank profits, which raises the risk of a recession (Aizenman & Pinto, 2021). Mishkin (2022) suggests an annual inflation target of 2–3%, which corresponds with this monthly amount. Greater growth rates of GDP over 3% encourage credit borrowing and lower repayment risks (Cerra & Saxena, 2017). When GDP grows by less than 1%, it makes everybody more likely to go into a crisis (Reinhart & Rogoff, 2009). A healthy monthly growth of the GDP figures varies from 1.39% to 1.91%, with shocks occurring under the condition of a growth rate below 0.87% (Mian & Sufi, 2020). This range provides best stability in the exchange rate, with MYR 3.49 and 3.80 as the highest average exchange rate points. Its rise above 4.10 is an indication of stress on the system in general (Eichengreen et al., 2020; Frankel, 2022; Obstfeld & Rogoff, 2021). A 0.33% fall of the stock market in value or composite index drop below −2.80 is more than a sign of systemic stress (Bekaert & Harvey, 2021; Schwert, 2020; Laeven & Valencia, 2018).

4.3 Visualization of Framework for Banking Resilience

Table 11 presents how well-performing Malaysia's banking sector is based on macroeconomic and local indicators. For crisis prediction and linkage accuracy (QPS), loss function, and resilience thresholds, we advocate a three-month indexation horizon. The maximum threshold indicates that the system is resilient to 94% of financial shocks, with QPS=0.18 and loss function=0.06. The loss function is 0.10 and at the same QPS, lower thresholds give 90% resilience. In resilience, even small change in the loss function makes a huge difference by low, which is why the loss function should be kept low for stability. The lower the QPS value, the better the model, so the more accurate the calibration, and value of a model is around 0 to 2. It appears that macroeconomic shock transmission can lead to a loss of 6.38% to 10.18%, and overall resilience varies from 90% to 94%.

Table 11: Visualization of banking resilience index

Indicator	Threshold	Accuracy (QPS)	Loss Function	Resilience Level
Banking Sector Resilience Index	Upper	0,18	0,06	94%
(3 months optimal time horizon)	Lower	0,18	0,10	90%

Source: The author's calculation

5. CONCLUSION

Banking resilience refers to the ability to withstand major economic shocks while maintaining strong operational fundamentals and financial stability. Key internal measures should remain in some range for adequate resilience: NPL to be between 0.98% and 1.22%, LDR to range from 80.02% to 81.48%, CAR to range from 14.75% to 16.21%, return on assets should range from 1.40% to 1.52%. Macroeconomic pressures start to mount when GDP growth falls below 0.87% per month, inflation goes above 0.24%, the MYR/USD rate can go over 4.10, and stock market declines rise above −0.33%. Shock transmission results in functional losses of 6.38% to 10.18%, while resilience remains between 90% and 94%. So, it is important to hold assets in balance, to finance wisely and to keep macroeconomic conditions stable. Close monitoring, with the support of an adaptive early warning system, reinforces the financial fundamentals and ensures that the resilience of banking fits into sustainable economic growth and targets of SDG 8.

6. LIMITATION OF STUDY

This study employs the Early Warning System (EWS) with signal extraction. For future research, logit analysis may produce new insights. The logit method can enable collecting risk elements and their probabilities, giving banks a unique perspective on their resilience and making resilience assessments more accurate and comprehensive because of the insights gained from it. Non-Performing Loans (NPL), Capital Adequacy Ratio (CAR), Loan-to-Deposit Ratio (LDR), and Return on Assets (ROA) are among the static thresholds used in the study. Future research might be guided by Investment Proportion and Risk (IPR), Liquid Assets Ratio (LA), Non-Core Deposits (NCD), Net Profit Margin (NPM), Net Operating Margin (NOM), and Cost-Income Ratio (CIR) for a closer examination of banking resilience. The current study assumes procyclicality to define the research period and explore how risk conditions vary dynamically over time; hence empirical testing is needed to evaluate whether the years selected for the study exhibit procyclical behavior.

REFERENCES

Abou-El-Sood H, El-Sayed D (2022), "Abnormal disclosure tone, earnings management and earnings quality". *Journal of Applied Accounting Research*, Vol. 23 No. 2 pp. 402–433, doi: https://doi.org/10.1108/JAAR-07-2020-0139

Afandi, M. A., Hartarto, R. B., & Usman, H. (2024). Effects of ability, benevolence, and integrity on banking trust during the COVID-19 pandemic in Indonesia. *International Journal of Business and Emerging Markets*, *16*(2), 207-221, doi: https://doi.org/10.1504/IJBEM.2024.137664

Aizenman, J., & Pinto, B. (2021). Inflation, deflation, and financial instability: Lessons from the great depression and recent global crises. *Journal of Monetary Economics, 117*, 1–15.

Al Rahahleh, N., Ishaq Bhatti, M., & Najuna Misman, F. (2019). Developments in risk management in Islamic finance: A review. *Journal of Risk and Financial Management, 12*(1), 37. https://doi.org/10.3390/jrfm12010037

Alsamara, M., Mrabet, Z., Saleh, A. S., & Anwar, S. (2018). The environmental Kuznets curve relationship: A case study of the Gulf Cooperation Council region. *Environmental Science and Pollution Research, 25*(33), 33183–33195. https://doi.org/10.1007/s11356-018-3161-1

Anastasiou, D., Louri, H., & Tsionas, M. (2019). Nonperforming loans in the Euro area: Are core–periphery banking markets fragmented? *International Journal of Finance & Economics, 24*(1), 97–112. https://doi.org/10.1002/ijfe.1651

Asyiqin, I. Z., & Rinaldi, Y. (2025). Local Government's role in Aceh's sharia banking transition: legal and institutional perspectives. *Legality : Jurnal Ilmiah Hukum*, *33*(1), 244–260. https://doi.org/10.22219/ljih.v33i1.39419

Athanasoglou, P. P., Brissimis, S. N., & Delis, M. D. (2008). *Bank-specific, industry-specific and macroeconomic determinants of bank profitability*. Journal of International Financial Markets, Institutions & Money, 18(2), 121–136. https://doi.org/10.1016/j.intfin.2006.07.001

Bank for International Settlements. (2009). *Strengthening the resilience of the banking sector: Consultative document.* Bank for International Settlements. https://www.bis.org

Bank Negara Malaysia. (2024a). *Bank Negara Malaysia.* https://www.bnm.gov.my/

Bank Negara Malaysia. (2024b). *Publication.* https://www.bnm.gov.my/publications/mhs

Barth, J. R., Caprio, G., & Levine, R. (2004). *Bank regulation and supervision: What works best?* Journal of Financial Intermediation, 13(2), 205–248. https://doi.org/10.1016/j.jfi.2003.06.002

Beck, T., Jakubik, P., & Piloiu, A. (2021). Non-performing loans: What matters in addition to the economic cycle? *Journal of Banking & Finance, 125*, 106–119.

Beck, T., & Keil, J. (2021). Are banks catching corona? Effects of Covid on lending in the U.S (SSRN Scholarly Paper 3805284). https://papers.ssrn.com/abstract=3805284

Bekaert, G., & Harvey, C. R. (2021). Emerging market finance. *Journal of Economic Perspectives, 35*(3), 77–98.

Bilgin, M. H., Danisman, G. O., Demir, E., & Tarazi, A. (2021). Economic uncertainty and bank stability: Conventional vs. Islamic banking. *Journal of Financial Stability, 56*, 100911. https://doi.org/10.1016/j.jfs.2021.100911

Briguglio, L. (2009). Conceptualising and measuring economic vulnerability and resilience. Tallinn University of Technology.

Brown, E. D., Anderson, K. E., Garnett, M. L., & Hill, E. M. (2019). Economic instability and household chaos relate to cortisol for children in poverty. *Journal of Family Psychology, 33*(6), 629–639. https://doi.org/10.1037/fam0000545

Cecchetti, S. G., & Tucker, P. (2016). Is there macroprudential policy without international cooperation? (SSRN Scholarly Paper 2717591). https://papers.ssrn.com/abstract=2717591

Cerra, M. V., & Saxena, M. S. C. (2017). Booms, crises, and recoveries: A new paradigm of the business cycle and its policy implications. International Monetary Fund.

Cukierman, A., Edwards, S., & Tabellini, G. (2020). Seigniorage and political instability. *American Economic Review, 110*(8), 2436–2450.

Department of Statistics Malaysia. (2024a). *Consumer prices.* https://open.dosm.gov.my

Department of Statistics Malaysia. (2024b). *Exchange rates.* https://open.dosm.gov.my

Department of Statistics Malaysia. (2024c). *Gross domestic product (GDP).* https://open.dosm.gov.my

Eichengreen, B., Hausmann, R., & Panizza, U. (2020). Currency mismatches, debt intolerance, and the original sin: Why they are not the same and why it matters. *Journal of International Money and Finance, 102*, 52–69.

Fatmawati, I., Irianda, A. G., & Abilawa, A. (2024). The Influence of Islamic Service Quality, Emotional Attachment, and Religiosity on Satisfaction for Loyalty in the Context of Sharia Banking. In *E3S Web of Conferences* (Vol. 571, p. 02005). EDP Sciences, https://doi.org/10.1051/e3sconf/202457102005

Fontela, E., & Gabus, A. (1976). The DEMATEL observer. Battelle Geneva Research Centre.

Frankel, J. A. (2022). No single currency regime is right for all countries or at all times. *Review of World Economics, 158*(1), 1–15.

Ghenimi, A., Chaibi, H., & Ftiti, Z. (2021). The effects of the COVID-19 pandemic on the risk-return trade-off in the banking sector: International evidence. *Journal of Economic Behavior & Organization, 186*, 60–77.

Hariyadi, E., Wong, W. K., & Johari, S. M. (2025). Promoting sustainable banking: the role of private credit in reducing CO_2 emissions in Indonesia. *International Journal of Energy Economics and Policy*, *15*, https://doi.org/10.32479/ijeep.18036

Huda, M., & Santosa, D. (2022). Effect of financing to deposit ratio (FDR) and operational efficiency ratio (OER) on return on assets (ROA) with non-performing financing (NPF) as an intervening variable. *Jurnal Ekonomi Islam Indonesia, 4*(2).

Ichsan, M., Fitriyanti, F., Setiorini, K. R., & Al-Qudah, A. M. A. (2024). Digitalization of Islamic banking in Indonesia: Justification and compliance to sharia principles. *Jurnal Media Hukum*, *31*(2), 244-261.

Iqbal, M., Sadeghi, M., & Farhadi, M. (2021). The effect of capital adequacy on financial stability in emerging markets: The case of Asian banking. *Emerging Markets Finance and Trade, 57*(11), 3217–3230.

Johari, S. M. (2024). Enhancing Ethic Integrity and Human Resource Development to Build a Green Banking Business Model in Indonesia. *Journal Of Optimization In Industrial Engineering*, *37*(2), 97.

Kamarudin, F., Sufian, F., & Nassir, A. M. (2021). How does the shadow economy affect non-performing loans? Empirical evidence from high shadow economy countries. *Finance Research Letters, 38*, 101–104.

Kaminsky, G. L. (1999). Currency and banking crises: The early warnings of distress. International Monetary Fund.

Kaminsky, G. L., & Reinhart, C. M. (1996). The twin crises: The causes of banking and balance-of-payments problems. *International Finance Discussion Papers, 544.* https://www.federalreserve.gov/econres/ifdp/the-twin-crises-the-causes-of-banking-and-balance-of-payments-problems.htm

Kusuma, D. B., & Duasa, J. (2016). Building an early warning towards the resilience of Islamic banking in Indonesia. *Al-Iqtishad: Journal of Islamic Economics, 9*(1), 13–32. https://doi.org/10.15408/aiq.v9i1.3881

Laeven, M. L., & Valencia, M. F. (2018). Systemic banking crises revisited. International Monetary Fund.

Lietaer, B. (2017). A possibly Shari'ah-compatible global currency to stabilize the monetary system. *Journal of King Abdulaziz University-Islamic Economics, 30*(2), 47–58. https://doi.org/10.4197/Islec.30-2.4

Loayza, N., Ouazad, A., & Rancière, R. (2018). Financial development, growth, and crisis: Is there a trade-off? In R. J. Caballero, K. N. Kuttner, & D. N. Gruen (Eds.), *Monetary policy in an uncertain world* (pp. 289–311). Edward Elgar Publishing.

Majid, N. H. A., Mohd Yusof, R., Abd. Wahab, N., Abdul Rahim, M. A. A., Wiranatakusuma, D. B., & Tasman, S. M. (2025). Understanding resilience of Islamic banking amid COVID-19: A systematic literature review of banking, macroeconomic, and risk factors. Journal of Islamic Accounting and Business Research. https://doi.org/10.1108/JIABR-10-2023-0356

Mawardi, I., Al Mustofa, M. U., Widiastuti, T., & Wahid, W. W. (2023). Early warning systems in Indonesian Islamic banks: A comparison of Islamic commercial and rural banks. *Cogent Economics & Finance, 11*(1), 2172803. https://doi.org/10.1080/23322039.2023.2172803

Mian, A., & Sufi, A. (2020). How does GDP growth influence financial stability? A global perspective. *Review of Finance, 24*(2), 305–332.

Mishkin, F. S. (2022). Inflation targeting: Lessons from the international experience. *Journal of Economic Perspectives, 36*(2), 45–68.

Nardo, M. (2005). Tools for composite indicators building. *European Commission Joint Research Centre, 15*(1), 19–20.

Nguyen, T. T. H., Pham, H. T., & Tran, D. N. (2020). The impact of capital adequacy on bank stability: A cross-country analysis in ASEAN. *Journal of Asian Finance, Economics and Business, 7*(9), 85–92.

Nkusu, M. M. (2020). Nonperforming loans and macrofinancial vulnerabilities in advanced economies. *IMF Working Papers, 2020*(1), 1–27.

Nugraheni, P., & Muhammad, R. (2024). The optimisation of Qardhul Hasan management in Islamic banking: enhancing its role in empowering the community. *Journal of*

Enterprising Communities: People and Places in the Global Economy, *18*(3), 469-486.

Obstfeld, M., & Rogoff, K. (2021). Revisiting speculative hyperinflations in monetary models. *Review of Economic Dynamics, 40*, 1-11.

Ozili, P. K. (2021). Bank profitability determinants: Comparing the United States, Nigeria and South Africa.

Pham, H. S. T., & Tran, H. T. (2020). CSR disclosure and firm performance: The mediating role of corporate reputation and moderating role of CEO integrity. *Journal of Business Research, 120*, 127-136.

Pratama, A., & Darmawan, A. (2023). Analyzing performance determinants: Islamic rural bank performance in Indonesia. *Journal of Islamic Economics and Social Sciences, 4*(1).

Pratiwi, A., Verani, T., & Rayhan, A. (2023). The Comparative Analysis of Financial Distress Precipitating Factors in Islamic Banking in Indonesia and Malaysia Based on Bankometer Variables. *Falah: Jurnal Ekonomi Syariah*, *8*(2), 32-46.

Rahman, A. A., & Shahimi, S. (2010). Credit risk and financing structure of Malaysian Islamic banks. *Journal of Economic Cooperation & Development, 31*(3), 83–105.

Reinhart, C. M., & Rogoff, K. S. (2009). The aftermath of financial crises. *American Economic Review, 99*(2), 466–472. https://doi.org/10.1257/aer.99.2.466

Saaty, T. L. (2008). The analytic hierarchy and analytic network measurement processes: Applications to decisions under risk. *European Journal of Pure and Applied Mathematics, 1*(1), 122-196.

Schwert, M. (2020). Does borrowing from banks cost more than borrowing from the market? *The Journal of Finance, 75*(2), 905-947.

Shehzad, K., Xiaoxing, L., & Kazouz, H. (2020). COVID-19's disasters are perilous than Global Financial Crisis: A rumor or fact? *Finance Research Letters, 36*, 101669.

Surwanti, A., & Wardana, R. (2024, February). The Effects of COVID-19 Pandemic on Banking Performance in Indonesia: Risk, Good Corporate Governance, Earnings, and Capital. In *International Congress on Information and Communication Technology* (pp. 313-324). Singapore: Springer Nature Singapore.

Tzeng, G. H., Chiang, C. H., & Li, C. W. (2007). Evaluating intertwined effects in e-learning programs: A novel hybrid MCDM model based on factor analysis and DEMATEL. *Expert Systems with Applications, 32*(4), 1028–1044.

Widodo, N. F. P. (2021, September). Pengaruh rasio NPF, CAR, OER, dan FDR terhadap kinerja keuangan perbankan syariah di Indonesia dan Malaysia. In *Prosiding Industrial Research Workshop and National Seminar* (Vol. 12, pp. 1554-1561).

Wiranatakusuma, D. B. (2018). Constructing Islamic banking resilience index in Indonesia. *Journal of Islamic Monetary Economics and Finance, 3*, 45-62.

Wiranatakusuma, D.B., Aprizal, A. (2025). Developing Islamic Banking Resilience in West Nusa Tenggara: Extraction Signal Approach. In: Qasem, I. (eds) Data-Driven Decision Making for Sustainable Business Growth. Studies in Systems, Decision and Control, vol 607. Springer, Cham. https://doi.org/10.1007/978-3-031-96530-2_57

Yahoo Finance. (2024). FTSE Bursa Malaysia KLCI (^KLSE) stock historical prices & data. https://finance.yahoo.com/quote/%5EKLSE/history/