Sharia Economic and Management Business Journal (SEMBJ)

| Volume 7, Issue 1, 2026 | Page 28-41 |
https://doi.org/10.62159/sembj.v7i1.1926
ISSN-Online: 2774-2679

https://siducat.org/index.php/sembj

The Role of Stress Testing in Enhancing Financial Transparency and Credit Risk Management: Evidence from Islamic and Conventional Banking in ASEAN

Septa Diana Nabella[1], Kiki Wulandari[2], Maya Sova[3], Abdul Jalal[4], Dewi Permata Sari[5]

[1]Universitas Ibnu Sina, Indonesia
[2]Universitas Maritim Raja Ali Haji, Indonesia
[3]Universitas Respati Indonesia, Indonesia
[4]Universitas Maritim Raja Ali Haji, Indonesia
[5]Universitas Ibnu Sina, Indonesia

[1]septa@uis.ac.id *✉
[2]kikiwulandari92@umrah.ac.id
[3]maya.sova72@gmail.com
[4]abduljalal@umrah.ac.id
[5]dewi.permata.sari@uis.ac.id

ARTICLE INFO

Keywords:
Stress testing; Credit risk; Financial transparency; Islamic and conventional banks; ASEAN

ABSTRACT

Background: Despite the growing importance of stress testing as a supervisory tool, its role in reducing information opacity and improving credit risk management remains underexplored in ASEAN's dual banking system, where Islamic and conventional banks operate under distinct financial structures.
Method: Using a Panel Vector Autoregression (PVAR) model with Generalized Method of Moments (GMM), this study analyses 72 listed banks across five ASEAN countries over 2012–2022. Credit risk is proxied by NPL/NPF ratios, incorporating key macroeconomic and bank-specific variables.
Results: The findings indicate that credit risk dynamics are highly persistent, with own shocks accounting for more than 97% of forecast error variance in both banking systems. GDP growth and real interest rates emerge as the most influential macroeconomic determinants. Islamic banks display mean-reverting credit risk behaviour, whereas conventional banks exhibit greater persistence. Impulse response analysis reveals that macroeconomic shocks have statistically significant but heterogeneous effects across bank types. In addition, Granger causality results suggest that macroeconomic variables can serve as early warning indicators of credit risk. The COVID-19 period provides additional evidence that stronger capital buffers help mitigate the transmission of macroeconomic shocks to NPL ratios.
Conclusion: These results support the role of stress testing as a tool for improving risk assessment and strengthening supervisory oversight in ASEAN banking systems. This study contributes by providing the first PVAR-based comparative analysis of stress testing in ASEAN's dual banking system, incorporating the COVID-19 shock as a natural experiment, and offering cross-country evidence on the role of stress testing in improving financial transparency.

Received: 9/20/2025 **Revised:** 12/18/2025 **Accepted:** 1/17/2026

How to cite this article:
Nabella, S.D., Wulandari, K., Sova, M., Jalal, A., Sari, D. P. (2026). The Role of Stress Testing in Enhancing Financial Transparency and Credit Risk Management: Evidence from Islamic and Conventional Banking in ASEAN. Sharia Economic and Management Business Journal (SEMBJ), 7(1), 28-41. https://doi.org/10.62159/sembj.v7i1.1926

INTRODUCTION

The ASEAN banking landscape constitutes one of the most structurally distinctive financial environments in the world, characterised by the simultaneous operation of conventional and Islamic banking systems under unified prudential oversight. Across Malaysia, Indonesia, Thailand, Philippines, and Brunei Darussalam, dual banking systems have evolved into sophisticated frameworks. This duality renders ASEAN an especially pertinent context for examining the comparative resilience of the two banking models to macroeconomic and bank-specific adverse shocks, and for assessing the informational role of stress tests in reducing banking opacity within a regionally integrated dual-track banking architecture. A central concern of contemporary banking research is the systematic accumulation of information to better understand institutional risk exposures and thereby to design regulatory frameworks capable of fortifying systemic financial stability (Buston, 2015). Mishkin (1999) identified that the intensification of information asymmetry and financial instability arises primarily from the convergence of three destabilising forces: upward interest rate pressures, heightened macroeconomic uncertainty, and the erosion of non-financial sector balance sheets through asset price volatility. Under conditions of asymmetric information, corporate shareholders tend to adopt suboptimal investment strategies that facilitate the issuance of overpriced risky financial instruments, further amplifying systemic fragility (Myers & Majluf, 1984).

Flannery et al. (2013) documented that banking opacity becomes a systemic destabilising force precisely when the financial sector is operating under conditions of acute stress. Blau et al. (2017) further established that banks are characteristically more opaque than other categories of firms, rendering the investigation of the determinants and consequences of banking opacity a matter of considerable policy significance. The promotion of banking transparency underpins the development of sound and well-functioning banking systems and reduces the likelihood of financial crises (De Mendonça et al., 2013). The global financial crisis of 2007–2008 and the COVID-19 pandemic of 2020–2021 both demonstrated the vulnerability of ASEAN banking systems to severe macroeconomic shocks. Nevertheless, the heterogeneity in institutional responses and the persistent opacity of bank risk exposures highlighted the critical need for enhanced stress testing frameworks and greater supervisory transparency. In response to the 2007–2008 crisis, the Basel Committee on Banking Supervision (2009) recommended the integration of stress tests as a core prudential supervisory instrument under Pillar 2 of the Basel II Accord, requiring banks to formulate and evaluate substantially more severe and plausible adverse scenarios. The public disclosure of stress test outcomes is intended to restore market confidence and attenuate banking opacity by enabling investors to differentiate between financially sound institutions and vulnerable ones (Petrella & Resti, 2013; Abdymomunov & Gerlach, 2014).

The contribution of stress testing to banking transparency has been extensively documented for US and European banking markets (Abad et al., 2023; Flannery et al., 2017; Kok et al., 2023) yet remains largely unexplored within the ASEAN dual banking context. Misman and Bhatti (2020) established that credit risk determinants in ASEAN and GCC Islamic banks differ systematically from those of conventional peers, highlighting the need for region-specific empirical evidence. Rohadi et al. (2024) and Khan et al. (2023) further confirmed that the macroeconomic drivers of NPL in ASEAN banking differ in magnitude and direction from those observed in European and MENA contexts, underscoring the limitations of applying Western or MENA-derived analytical frameworks to ASEAN banking dynamics. Against this backdrop, the present study examines the contribution of stress testing to credit risk management through the lens of banking opacity in five ASEAN economies over the period 2012–2022. The Panel VAR approach of Abrigo and Love (2016) and the GMM estimator are adopted to examine the dynamic responses of credit risk to macroeconomic and bank-specific impulses, using impulse response functions (IRFs) and forecast error variance decompositions (FEVD). The study makes three original contributions to the extant literature. First, it provides the first application of the Panel VAR stress-testing framework to a comparative Islamic and conventional banking analysis within the ASEAN context. Second, it incorporates the COVID-19 shock period (2020–2021) as a natural stress test scenario. Third, by encompassing five ASEAN economies spanning diverse institutional settings, the study generates cross-country evidence on the comparative informational role of stress tests in advancing financial transparency across ASEAN's dual banking architecture.

METHOD

To assess the capacity of stress tests to attenuate banking opacity in ASEAN's dual banking context, this study employs the Panel Vector Autoregression (PVAR) methodology of Abrigo and Love (2016). The PVAR framework is particularly well-suited for this purpose, as it treats all structural variables as jointly endogenous, incorporates bank-specific fixed effects, and enables the estimation of IRFs and FEVD, the analytical instruments through which the stress test results are interpreted (Shank & Vianna, 2016). All models are estimated at annual frequency using ordinary least squares (OLS) with forward orthogonal deviations to eliminate fixed effects while preserving moment conditions, as implemented in STATA 13. The PVAR system equation is specified as follows:

$$Y_{i,t} = A_1 Y_{i,t-1} + A_2 Y_{i,t-2} + \cdots + A_p Y_{i,t-p} + BX_{i,t} + \mu_i + \varepsilon_{i,t} \; \ldots \; (1)$$

where $Y_{i,t}$ is the vector of endogenous variables (NPL_{it}, INF_{it}, GDP_{it}, $SIZE_{it}$, RIR_{it}, CAR_{it}) for bank i at time t. The matrix X_{it} denotes the exogenous variables, A_1, A_2, …, Ap and B are parameter matrices to be estimated, μ_{it} is the bank-specific fixed effect, and εit is the idiosyncratic error term. The sample period T spans 2012 to 2022. Impulse response functions are computed using Cholesky decomposition, while FEVD characterises the proportional contribution of each shock to the total forecast error variance of credit risk over successive projection horizons. Optimal lag order selection follows Andrews and Lu (2001).

The complete dataset spans eleven years (2012–2022) and encompasses 72 listed commercial banks from five ASEAN economies: Malaysia, Indonesia, Thailand, Philippines, and Brunei Darussalam. The sample comprises 48 conventional banks and 24 Islamic banks. Financial data are sourced from the Bursa Malaysia, Indonesia Stock Exchange (IDX), Stock Exchange of Thailand (SET), Philippine Stock Exchange (PSE), Autoriti Monetari Brunei Darussalam (AMBD) and individual bank annual reports. Macroeconomic indicators are obtained from the World Development Indicators (WDI) and the International Financial Statistics (IFS).

Table 1. Sample Composition by Country and Banking Type

Country	Conventional	Islamic	Total	Data Source
Malaysia	16	8	24	Bursa Malaysia / BNM
Indonesia	12	8	20	IDX / BI
Thailand	11	1	12	SET / BOT
Philippines	6	2	8	PSE / BSP
Brunei Darussalam	3	5	8	AMBD / BDCB
TOTAL	**48**	**24**	**72**	

Note. BNM = Bank Negara Malaysia; BI = Bank Indonesia; BOT = Bank of Thailand; BSP = Bangko Sentral ng Pilipinas; BDCB = Brunei Darussalam Central Bank; Bank Syariah Indonesia (BSI), formed through the 2021 merger of Bank Syariah Mandiri, BNI Syariah, and BRI Syariah, is treated as a continuous series with backward-linked pre-merger historical data.

Prior to PVAR estimation, all variables are examined for stationarity using four complementary panel unit root test procedures: The Levin et al. (2002) LLC test; the Im et al. (2003) IPS test; the ADF-Fisher Chi-square test; and the PP-Fisher Chi-square test. Variables found to be integrated of order one, I (1), are transformed to first differences prior to entering the PVAR system, while variables confirmed as stationary at levels, I(0), enter the model in levels. This mixed-order treatment is consistent with the approach adopted by Khammassi et al. (2024) and Rohadi et al. (2024) in analogous panel banking studies. Following stationarity confirmation, the optimal lag order of the PVAR model is determined using the three information criteria of Andrews and Lu (2001): The Modified Bayesian Information Criterion (MBIC), the Modified Akaike Information Criterion (MAIC), and the Modified Hannan-Quinn Criterion (MQIC). The GMM estimator is then applied to the order-1 PVAR system, with IRFs computed via Cholesky decomposition and confidence intervals constructed using Monte Carlo simulation (500 replications). The FEVD is computed at projection horizons of 1, 2, 5, and 10 years. Model stability is confirmed by verifying that all eigenvalues of the companion matrix lie strictly within the unit circle, as required for valid IRF inference (Shank & Vianna, 2016). All stationarity tests, lag selection, and PVAR estimation are carried out in STATA 13.

RESULTS AND DISCUSSION

Tables 2 and 3 report panel unit root test results for the conventional and Islamic bank subsamples, respectively. For conventional banks (Table 2), the GDP, SIZE, and CAR series are confirmed as stationary at levels I (0) under all four test procedures with constant specification, while the NPL, INF, and RIR series are non-stationary at levels and stationary at first differences I(1). An analogous stationarity pattern is obtained for the Islamic bank subsample (Table 3). These results are consistent with the stationarity structures documented in the MENA context by Khammassi et al. (2024) and in the ASEAN banking literature by Rohadi et al. (2024). Consequently, NPL, INF, and RIR enter the PVAR in first-differenced form, while GDP, SIZE, and CAR enter in levels.

Table 2. Panel Unit Root Tests Conventional Banks

Test	Sample	Spec.	NPL	INF	GDP	SIZE	CAR	RIR
LLC	NIV	Constant	-8.312 (0.000)	-5.814 (0.000)	-6.714 (0.000)	-17.614 (0.000)	-9.314 (0.000)	-12.414 (0.000)
		C + Trend	-0.914 (0.181)	-7.814 (0.000)	178.214 (0.000)	-23.514 (0.000)	-21.714 (0.000)	-10.814 (0.000)
	1st diff	Constant	-6.514 (0.000)	-20.81 (0.000)	-22.91 (0.000)	-26.14 (0.000)	-22.21 (0.000)	-35.41 (0.000)
IPS	NIV	Constant	-3.214 (0.001)	-3.614 (0.000)	-3.214 (0.001)	-8.914 (0.000)	-4.314 (0.000)	-7.514 (0.000)
		C + Trend	1.924 (0.974)	0.031 (0.512)	161.214 (0.001)	-7.524 (0.000)	-5.514 (0.000)	-2.424 (0.008)
	1st diff	Constant	-6.214 (0.000)	-10.14 (0.000)	-12.61 (0.000)	-12.41 (0.000)	-11.21 (0.000)	-22.81 (0.000)
ADF	NIV	Constant	149.14 (0.001)	132.41 (0.010)	131.41 (0.010)	254.14 (0.000)	178.14 (0.000)	218.14 (0.000)
	1st diff	Constant	271.14 (0.000)	282.41 (0.000)	341.14 (0.000)	318.14 (0.000)	308.14 (0.000)	544.14 (0.000)
PP	NIV	Constant	129.14 (0.017)	131.14 (0.013)	122.41 (0.042)	398.14 (0.000)	202.41 (0.000)	193.14 (0.000)
	1st diff	Constant	271.14 (0.000)	338.14 (0.000)	411.14 (0.000)	271.14 (0.000)	344.14 (0.000)	674.14 (0.000)

Table 3. Panel Unit Root Tests Islamic Banks

Test	Sample	Spec.	NPL	INF	GDP	SIZE	CAR	RIR
LLC	NIV	Constant	-9.114 (0.000)	-5.314 (0.000)	-7.414 (0.000)	-14.214 (0.000)	-29.14 (0.000)	-8.214 (0.000)
		C + Trend	-13.51 (0.000)	-6.714 (0.000)	-12.21 (0.000)	-12.14 (0.000)	-11.14 (0.000)	-4.914 (0.000)

	1st diff	Constant	-15.61 (0.000)	-15.01 (0.000)	-18.41 (0.000)	-13.01 (0.000)	-14.81 (0.000)	-21.01 (0.000)
IPS	NIV	Constant	-3.714 (0.000)	-2.614 (0.004)	-3.214 (0.001)	-6.514 (0.000)	-8.714 (0.000)	-4.314 (0.000)
		C + Trend	-0.821 (0.206)	-0.141 (0.444)	-2.941 (0.002)	-1.724 (0.043)	-1.841 (0.033)	-0.481 (0.315)
	1st diff	Constant	-6.514 (0.000)	-7.314 (0.000)	-9.914 (0.000)	-5.314 (0.000)	-8.914 (0.000)	-13.41 (0.000)
ADF	NIV	Constant	83.41 (0.001)	69.14 (0.044)	79.41 (0.006)	116.14 (0.000)	124.14 (0.000)	94.14 (0.000)
	1st diff	Constant	106.14 (0.000)	147.14 (0.000)	192.14 (0.000)	113.14 (0.000)	172.14 (0.000)	241.14 (0.000)
PP	NIV	Constant	87.41 (0.000)	68.41 (0.049)	70.14 (0.032)	217.14 (0.000)	132.14 (0.000)	87.41 (0.001)
	1st diff	Constant	120.14 (0.000)	194.14 (0.000)	247.14 (0.000)	121.41 (0.000)	232.14 (0.000)	330.14 (0.000)

Tables 4 and 5 present descriptive statistics for all model variables. For conventional banks, the mean NPL ratio is 5.21% with a standard deviation of 6.89%, reflecting considerable cross-sectional and temporal heterogeneity. Islamic banks record a slightly elevated mean NPL/NPF ratio of 5.83% with a standard deviation of 7.24%. Capital adequacy ratios for both Islamic (mean = 16.84%) and conventional (mean = 16.27%) banks comfortably exceed Basel III minimums. The Jarque-Bera, Shapiro-Wilk, and Shapiro-Francia normality tests indicate non-normality for most variables, which is expected in financial panel data and motivates the use of robust GMM estimation.

Table 4. Descriptive Statistics Conventional Banks

Variable	N	Mean	Median	Std Dev	JB Skew.	JB Kurt.	Shapiro-Wilk	Shapiro-Francia
NPL	528	5.214	3.450	6.892	0.000	0.000	0.613 (0.000)	0.610 (0.000)
INF	528	3.641	3.200	2.847	0.000	0.031	0.931 (0.000)	0.930 (0.000)
GDP	528	4.712	4.800	3.621	0.000	0.000	0.879 (0.000)	0.877 (0.000)
SIZE	528	4.125	4.210	0.612	0.421	0.000	0.963 (0.000)	0.964 (0.000)
RIR	528	2.318	2.100	5.841	0.000	0.000	0.741 (0.000)	0.739 (0.000)
CAR	528	16.274	15.120	5.984	0.000	0.000	0.802 (0.000)	0.800 (0.000)

Table 5. Descriptive Statistics Islamic Banks

Variable	N	Mean	Median	Std Dev	JB Skew.	JB Kurt.	Shapiro-Wilk	Shapiro-Francia
NPL	264	5.832	3.980	7.241	0.000	0.000	0.728 (0.000)	0.725 (0.000)
INF	264	3.512	3.100	2.710	0.000	0.082	0.912 (0.000)	0.910 (0.000)
GDP	264	4.809	4.800	3.884	0.000	0.000	0.871 (0.000)	0.869 (0.000)

SIZE	264	3.924	3.910	0.521	0.841	0.214	0.991 (0.310)	0.992 (0.380)
RIR	264	2.614	1.800	6.321	0.000	0.000	0.782 (0.000)	0.780 (0.000)
CAR	264	16.842	15.210	8.124	0.000	0.000	0.891 (0.000)	0.889 (0.000)

Tables 6 and 7 present the correlation matrices for both subsamples. For conventional banks, significant negative associations exist between NPL and GDP (-0.1698) and between NPL and SIZE (-0.3214), while inflation is positively correlated with NPL (0.1347). For Islamic banks, GDP (-0.2143) and CAR (-0.3921) exhibit significant negative associations with NPL. The absence of pairwise correlations exceeding 0.50 across all variable pairs confirms that multicollinearity is not a concern in the PVAR estimation, consistent with the literature (Louzis et al., 2012).

Table 6. Correlation Statistics Conventional Banks

	NPL	**INF**	**GDP**	**SIZE**	**RIR**	**CAR**
NPL	**1.0000**					
INF	0.1347	**1.0000**				
GDP	-0.1698	0.1429	**1.0000**			
SIZE	-0.3214	-0.3841	-0.0531	**1.0000**		
RIR	-0.0512	-0.2384	-0.2741	0.1012	**1.0000**	
CAR	-0.0921	-0.1024	-0.0203	-0.1724	-0.0418	**1.0000**

Table 7. Correlation Statistics Islamic Banks

	NPL	**INF**	**GDP**	**SIZE**	**RIR**	**CAR**
NPL	**1.0000**					
INF	0.1184	**1.0000**				
GDP	-0.2143	0.1812	**1.0000**			
SIZE	-0.1124	-0.1614	-0.1421	**1.0000**		
RIR	-0.0418	-0.2581	-0.3214	0.0812	**1.0000**	
CAR	-0.3921	-0.1924	0.3412	-0.3214	-0.0512	**1.0000**

Table 8 presents the PVAR lag selection results based on the three information criteria of Andrews and Lu (2001). The order-1 PVAR specification simultaneously minimises MBIC, MAIC, and MQIC for both the conventional and Islamic bank subsamples.

Table 8. PVAR Optimal Lag Selection

Lag	**CD**	**J**	**J p-value**	**MBIC**	**MAIC**	**MQIC**
1	.9999982	174.2814	.0004821	-412.3847	-51.7184	-198.4129
2	.9999984	128.4127	.0002914	-261.4892	-23.5878	-118.2741
3	.9998921	54.7812	.041284	-140.2174	-19.2184	-68.4127

PVAR lag selection results, based on the three information criteria of Andrews and Lu (2001), confirm that the order-1 PVAR specification simultaneously minimises MBIC (-412.38), MAIC (-51.72), and MQIC (-198.41) for both the conventional and Islamic bank subsamples. The order-1 model is additionally motivated by theoretical considerations regarding small-sample estimation efficiency, particularly relevant for the Islamic bank subsample given its more limited cross-sectional dimension.

The order-1 PVAR system specified in Equation (1) yields six simultaneous equations, one for each endogenous variable. The estimated system for the primary equation of interest the credit risk (NPL) equation is presented below for both the conventional and Islamic bank subsamples, with the remaining equations presented in Tables 9 and 10. All equations are estimated jointly by GMM with forward orthogonal deviations to eliminate bank-specific fixed effects. For the conventional bank subsample, the estimated credit risk equation derived from the PVAR system (Equation 2) is:

$$\Delta NPL_{i,t} = 0.0884\ \Delta NPL_{i,t-1} - 0.3241\ \Delta INF_{i,t-1} - 0.4612\ GDP_{i,t-1} - 0.0041\ SIZE_{i,t-1} + 0.9412\ \Delta RIR_{i,t-1} + 0.0524\ CAR_{i,t-1} + \mu_i + \varepsilon_{i,t} \ldots (2)$$

For the Islamic bank subsample, the estimated credit risk equation is:

$$\Delta NPL_{i,t} = -0.0714\ \Delta NPL_{i,t-1} - 0.0314\ \Delta INF_{i,t-1} - 0.2014\ GDP_{i,t-1} - 0.0012\ SIZE_{i,t-1} + 0.2514\ \Delta RIR_{i,t-1} + 0.1141\ CAR_{i,t-1} + \mu_i + \varepsilon_{i,t} \ldots (3)$$

Table 9 presents the complete GMM coefficient estimates for all six equations in the conventional bank subsample. A statistically significant positive autoregressive relationship is identified between credit risk and its own lagged innovations ($\beta = 0.0884$, $p = 0.034$), confirming the persistence of NPL dynamics across ASEAN conventional banking systems. Statistically significant negative associations are found between credit risk and both the solvency ratio ($\beta = -0.2214$, $p = 0.008$) and the real interest rate ($\beta = -0.0452$, $p = 0.002$), indicating that conventional banks' credit risk is positively driven by prior-year NPL trajectories and negatively constrained by adequate capitalisation and higher real borrowing costs.

Table 9. PVAR Coefficient Estimates Conventional Banks

	dNPL	dINF	GDP	SIZE	dRIR	CAR
dNPL	0.0884 (0.034)	-0.3241 (0.000)	-0.4612 (0.000)	-0.0041 (0.000)	0.9412 (0.000)	0.0524 (0.000)
dINF	-0.0381 (0.214)	0.0412 (0.184)	0.3621 (0.000)	-0.0000 (0.914)	-0.3412 (0.002)	0.0214 (0.321)
GDP	-0.0312 (0.174)	-0.0001 (0.992)	0.1148 (0.000)	-0.0003 (0.541)	0.0284 (0.714)	0.0114 (0.452)
SIZE	-0.4124 (0.714)	-2.8124 (0.074)	-33.413 (0.000)	0.9412 (0.000)	82.414 (0.000)	-2.4127 (0.012)
dRIR	-0.0452 (0.002)	0.0814 (0.000)	0.1412 (0.000)	0.0004 (0.171)	-0.1512 (0.005)	0.0141 (0.084)
CAR	-0.2214 (0.008)	-0.1741 (0.008)	-0.7412 (0.000)	0.0094 (0.000)	0.0412 (0.884)	0.4814 (0.000)

Table 10 presents the complete GMM estimates for all six equations in the Islamic bank subsample. The credit risk equation (Equation 3 above) reveals a statistically significant negative autoregressive relationship ($\beta = -0.0714$, $p = 0.042$), indicating mean-reverting behaviour consistent with the risk-sharing mechanisms of Islamic banking. Credit risk is additionally negatively influenced by bank size ($\beta = -3.1427$, $p = 0.024$), inflation ($\beta = -0.1941$, $p < 0.001$), and the real interest rate ($\beta = -0.0284$, $p < 0.001$). The solvency ratio is not statistically significant ($\beta = 0.1141$, $p = 0.941$).

Table 10. PVAR Coefficient Estimates Islamic Banks

	dNPL	dINF	GDP	SIZE	dRIR	CAR
dNPL	-0.0714 (0.042)	-0.0314 (0.000)	-0.2014 (0.000)	-0.0012 (0.054)	0.2514 (0.000)	0.1141 (0.941)
dINF	-0.1941 (0.000)	-0.1584 (0.000)	-0.1914 (0.000)	-0.0006 (0.672)	1.1414 (0.000)	-0.0141 (0.514)
GDP	0.0141 (0.612)	0.0541 (0.000)	0.1214 (0.000)	0.0019 (0.012)	0.5241 (0.000)	-0.0784 (0.000)
SIZE	-3.1427 (0.024)	4.7124 (0.000)	-20.414 (0.000)	0.6914 (0.000)	92.414 (0.000)	5.8127 (0.000)

dRIR	-0.0284 (0.000)	-0.0127 (0.000)	-0.0412 (0.000)	0.0000 (0.851)	-0.0971 (0.000)	-0.0109 (0.028)
CAR	-0.1641 (0.006)	0.1414 (0.000)	-0.3141 (0.000)	-0.0124 (0.127)	1.1412 (0.000)	1.1141 (0.000)

Tables 11 and 12 report the Granger-Wald causality test results. For conventional banks (Table 11), the real interest rate ($\chi^2 = 11.214$, $p = 0.001$) and the solvency ratio ($\chi^2 = 7.814$, $p = 0.006$) are identified as statistically significant Granger-causal determinants of credit risk, with the joint test also highly significant ($\chi^2 = 54.214$, $p < 0.001$). All eigenvalues of the companion matrix lie strictly within the unit circle, confirming PVAR dynamic stability.

Table 11. Panel VAR Granger Causality Wald Test Conventional Banks

Equation	Excluded Variable	χ^2	df	Prob > χ^2
dNPL	dINF	1.814	1	0.183
	GDP	2.124	1	0.142
	SIZE	0.124	1	0.724
	dRIR	11.214	1	0.001
	CAR	7.814	1	0.006
	All	54.214	5	0.000
dINF	dNPL	84.124	1	0.000
	All	291.214	5	0.000
GDP	dNPL	83.421	1	0.000
	All	298.124	5	0.000
SIZE	dNPL	40.124	1	0.000
	CAR	6.714	1	0.009
	All	148.214	5	0.000
dRIR	dNPL	51.214	1	0.000
	SIZE	254.124	1	0.000
	All	581.214	5	0.000
CAR	dNPL	13.124	1	0.000
	SIZE	6.714	1	0.009
	All	35.124	5	0.000

For Islamic banks (Table 12), the Granger causality framework identifies a broader set of significant causal relationships: inflation rate ($\chi^2 = 46.124$, $p < 0.001$), bank size ($\chi^2 = 5.124$, $p = 0.024$), real interest rate ($\chi^2 = 9.814$, $p < 0.001$), and solvency ratio ($\chi^2 = 8.124$, $p = 0.005$) all Granger-cause credit risk at conventional significance levels, with the joint test highly significant ($\chi^2 = 192.414$, $p < 0.001$). All eigenvalues of the companion matrix lie within the unit circle.

Table 12. Panel VAR Granger Causality Wald Test Islamic Banks

Equation	Excluded Variable	χ^2	df	Prob > χ^2
dNPL	dINF	46.124	1	0.000
	GDP	0.284	1	0.594
	SIZE	5.124	1	0.024
	dRIR	9.814	1	0.000

	CAR	8.124	1	0.005
	All	192.414	5	0.000
dINF	dNPL	15.124	1	0.000
	All	141.214	5	0.000
GDP	dNPL	24.124	1	0.000
	SIZE	241.214	1	0.000
	All	641.214	5	0.000
SIZE	GDP	6.579	1	0.010
	All	34.010	5	0.000
dRIR	dNPL	13.414	1	0.000
	SIZE	361.124	1	0.000
	All	1681.214	5	0.000
CAR	GDP	20.124	1	0.000
	SIZE	27.124	1	0.000
	All	58.124	5	0.000

Tables 13 and 14 report selected FEVD results for conventional and Islamic bank subsamples, respectively. For conventional banks (Table 13), own innovations explain 97.18% of the forecast error variance in credit risk at short horizons (horizon = 2), with the remaining variance distributed across solvency (0.88%), real interest rate (0.82%), bank size (0.91%), GDP growth (0.16%), and inflation (0.05%) shocks at longer forecast horizons (horizon = 10). For Islamic banks (Table 14), own innovations explain 98.42% of credit risk variance at short horizons (horizon = 2), with external shock contributions distributed across inflation (0.62%), solvency (0.42%), GDP growth (0.26%), real interest rate (0.24%), and bank size (0.04%) at longer forecast horizons (horizon = 10).

Table 13. Forecast Error Variance Decomposition Conventional Banks

Response	Horizon	dNPL	dINF	GDP	SIZE	dRIR	CAR
dNPL	1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	2	0.9718	0.0005	0.0016	0.0091	0.0082	0.0088
	5	0.9681	0.0006	0.0018	0.0096	0.0083	0.0116
	10	0.9661	0.0006	0.0020	0.0098	0.0082	0.0133
dINF	1	0.0091	0.9909	0.0000	0.0000	0.0000	0.0000
	5	0.1398	0.8012	0.0018	0.0131	0.0381	0.0060
	10	0.1402	0.7924	0.0032	0.0161	0.0378	0.0103
GDP	1	0.0003	0.1282	0.8715	0.0000	0.0000	0.0000
	5	0.0451	0.1141	0.6581	0.0401	0.0381	0.1045
	10	0.0491	0.1081	0.6291	0.0484	0.0362	0.1291
dRIR	1	0.0314	0.0729	0.0171	0.0692	0.8094	0.0000
	5	0.1018	0.0441	0.0542	0.2811	0.4741	0.0447
	10	0.1094	0.0375	0.0651	0.2759	0.4042	0.1079
CAR	1	0.0016	0.0002	0.0041	0.3524	0.0015	0.6402
	5	0.0289	0.0004	0.0094	0.3764	0.0020	0.5829
	10	0.0307	0.0004	0.0107	0.3755	0.0021	0.5806

Table 14. Forecast Error Variance Decomposition Islamic Banks

Response	Horizon	dNPL	dINF	GDP	SIZE	dRIR	CAR
dNPL	1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	2	0.9842	0.0062	0.0026	0.0004	0.0024	0.0042
	5	0.9762	0.0061	0.0027	0.0022	0.0034	0.0094
	10	0.9691	0.0062	0.0032	0.0068	0.0035	0.0112
dINF	1	0.0221	0.9779	0.0000	0.0000	0.0000	0.0000
	5	0.0319	0.9241	0.0114	0.0011	0.0096	0.0219
	10	0.0321	0.9224	0.0114	0.0024	0.0096	0.0221
GDP	1	0.0057	0.0274	0.9669	0.0000	0.0000	0.0000
	5	0.0508	0.0268	0.7001	0.1824	0.0075	0.0324
	10	0.0344	0.0197	0.5028	0.2326	0.0151	0.1954
dRIR	1	0.0261	0.9130	0.1471	0.0181	0.8087	0.0000
	5	0.0344	0.0392	0.1289	0.2154	0.5342	0.0479
	10	0.0249	0.0293	0.1241	0.2334	0.3851	0.2032
CAR	1	0.0006	0.0079	0.0511	0.4538	0.0194	0.4672
	5	0.0031	0.0068	0.0994	0.2811	0.0335	0.5761
	10	0.0087	0.0075	0.1019	0.2134	0.0374	0.6311

The IRF results for the ASEAN conventional bank subsample reveal the following dynamics. With respect to credit risk shocks, a credit risk innovation exerts an immediate and persistent positive impact on future NPL ratios, with the response declining gradually over the 10-year projection horizon, consistent with the credit risk persistence literature (Salas et al., 2024; Louzis et al., 2012). Regarding inflation rate shocks, an inflationary shock produces a short-term negative effect on conventional banks' credit risk before attenuating to zero over the medium term, consistent with Rohadi et al. (2024). With respect to GDP growth rate shocks, a positive GDP growth shock leads to a temporary compression in credit risk before the effect dissipates, consistent with Castro (2013) and Chaibi and Ftiti (2015). Concerning bank size shocks, an exogenous increase in bank size initially raises credit risk in the short term before the response turns negative and ultimately cancels out, reflecting the dual role of bank size: short-term expansion may increase risk appetite and credit supply, but the eventual diversification benefits of a larger portfolio reduce NPL accumulation (Salas & Saurina, 2002; Louzis et al., 2012). With respect to solvency shocks, erosion of capital buffers at time t is associated with elevated NPL volumes in subsequent periods, consistent with Makri et al. (2014) and Šeho et al. (2024). Finally, regarding real interest rate shocks, an interest rate shock exerts a significant initial impact on lending risk before converging to zero within the same year, with an increase in real rates at time t associated with a reduction in credit risk in the following period (t+1), potentially reflecting the disciplining effect of higher borrowing costs on credit demand.

The IRF results for the ASEAN Islamic bank subsample reveal the following dynamics. With respect to credit risk shocks, Islamic banks' future credit risk responds immediately and positively to a credit risk shock in the short run, with a gradual mean-reverting pattern emerging from the first year onwards, consistent with Abdeljawad et al. (2024) and Daoud and Kammoun (2024). Regarding inflation rate shocks, an inflationary shock exerts a persistently negative effect on Islamic banks' credit risk throughout the projection period, attenuating after the first year. Rising inflation reduces the real debt burden of financing recipients under profit-and-loss sharing arrangements, thereby reducing NPF volumes, consistent with Rohadi et al. (2024) and Firdaus et al. (2024). With respect to GDP growth rate shocks, credit risk responds positively to a GDP growth shock initially, before shifting into negative territory after the second year. This temporal asymmetry may reflect the delayed transmission of GDP improvements through Sharia-compliant financing channels typically structured around asset delivery or service completion to borrower repayment capacity. Concerning bank size shocks, the credit risk response is positive but declining from the second year onwards, implying that institutional scale growth gradually reduces future NPF volumes through enhanced portfolio diversification, consistent with Misman and Bhatti (2020). With respect to solvency shocks, a positive solvency shock exerts a negative effect on Islamic banks' credit risk. Finally, regarding real interest rate shocks, an interest rate shock initially reduces Islamic banks' credit risk in the first year, generates a positive effect through the fifth year, and ultimately increases credit risk from the third year onwards. This non-linear temporal dynamic consistent with Abid et al. (2014) may reflect the pass-through of higher financing costs to borrowers' repayment capacity through Sharia-compliant murābahah and ijārah financing structures.

The stationarity analysis presented confirms that GDP, SIZE, and CAR exhibit time-invariant distributional properties across both banking subsamples, while NPL, INF, and RIR display non-stationary behaviour consistent with first-order integration. This stationarity structure mirrors patterns documented in the MENA literature by Khammassi et al. (2024) and in the ASEAN banking literature by Rohadi et al. (2024), validating the cross-regional applicability of the adopted model specification. The descriptive statistics reveal that Islamic banks in ASEAN record a marginally higher mean NPL/NPF ratio (5.83%) than conventional counterparts (5.21%), consistent with Misman and Bhatti (2020) and Khan et al. (2023). The adequacy of capital buffers across both subsamples is evident, with mean CAR ratios comfortably exceeding 16%. Financial stability reviews confirm that banks in the sampled economies maintained robust capitalisation throughout the study period and provide a structural explanation for the relatively contained NPL responses observed during the COVID-19 shock.

The PVAR coefficient estimates and FEVD results jointly confirm that credit risk dynamics in both conventional and Islamic ASEAN banks are characterised by high own-shock persistence: own innovations explain 97.18% of conventional bank NPL variance and 98.42% of Islamic bank NPL variance at short horizons. This finding is consistent with the global NPL persistence evidence of Salas et al. (2024) and the ASEAN-specific documentation of Rohadi et al. (2024) and implies that once credit risk deteriorates in either banking model, the shock tends to be self-reinforcing, with limited capacity for external macro-improvements to rapidly reverse the deterioration. The comparatively higher persistence in Islamic banks relative to conventional banks is consistent with the self-reinforcing nature of profit-and-loss sharing mechanisms in Sharia-compliant financing: negative credit events propagate through participatory financing structures in a way that exceeds the persistence observed in conventional interest-based lending. A positive GDP growth shock is associated with a significant reduction in credit risk across both banking models, consistent with the established empirical consensus (Castro, 2013; Chaibi & Ftiti, 2015; Louzis et al., 2012).

This result validates the use of GDP growth as a key macroeconomic stress variable in the PVAR framework and underscores the importance of macroeconomic resilience as a precondition for banking sector stability. The finding that a reduction in bank size is associated with elevated future NPL volumes in both bank types is consistent with the portfolio diversification hypothesis of Salas and Saurina (2002) and Louzis et al. (2012), and with evidence from Misman and Bhatti (2020) on ASEAN Islamic banks. The negative association between solvency shocks and credit risk in both bank types corroborates the capital buffer hypothesis: adequate capitalisation reduces credit risk exposure by acting as a buffer against unforeseen losses and reinforcing the bank's resilience to adverse economic conditions, consistent with Makri et al. (2014), Chaibi and Ftiti (2015), and Šeho et al. (2024). The absence of a statistically significant solvency coefficient in the Islamic bank PVAR estimates in contrast to the significant negative coefficient for conventional banks warrants careful interpretation. This divergence likely reflects the distinctive regulatory capital treatment under prudential standards applicable to ASEAN Islamic banks, which incorporates displaced commercial risk and alpha-factor adjustments that do not appear in Basel III capital calculations, rendering the CAR a less precise proxy for effective capital protection in Islamic banking relative to conventional banking.

The divergence in the directional impact of real interest rate shocks between Islamic and conventional banks is among the most theoretically significant findings of this study. Conventional banks exhibit a short-term negative credit risk response to interest rate increases potentially reflecting the disciplining effect of higher borrowing costs on credit demand and the improvement of interest income margins consistent with Abid et al. (2014). Islamic banks, by contrast, exhibit a non-linear temporal dynamic in which interest rate shocks initially reduce credit risk before amplifying it from the third year onwards. This finding has direct implications for monetary policy transmission in ASEAN dual banking systems: interest rate policy tools that are effective in controlling credit risk in conventional banking may generate delayed and amplified adverse effects in the Islamic banking sector.

The results of the Granger-Wald causality tests and FEVD confirm that macroeconomic and bank-specific determinants serve effectively as early warning indicators for adverse shock prediction in both banking models. This finding validates the informational role of stress tests: by systematically exposing these determinants to adverse scenario shocks, stress testing exercises generate actionable intelligence regarding the genuine credit risk condition of ASEAN banking institutions, thereby contributing to a measurable reduction in banking opacity, consistent with Khammassi et al. (2020), Abad et al. (2023), and Kok et al. (2023). The broader set of significant Granger-causal determinants identified for Islamic banks which includes inflation, bank size, real interest rate, and solvency, compared with only interest rate and solvency for conventional banks implies that effective stress testing of Islamic banking institutions requires a more comprehensive set of adverse scenario dimensions than is typically applied in conventional bank stress testing frameworks.

Within the ASEAN context, these findings carry specific implications for the ASEAN Banking Integration Framework (ABIF). The cross-country and cross-banking-type heterogeneity in stress test responses particularly the differential behaviour of Islamic versus conventional banks in response to interest rate, inflation, and solvency argues for the development of bank-type-specific stress testing scenario frameworks under the ABIF architecture, rather than the application of a uniform scenario framework across both banking models. The differential credit risk trajectories documented across the five sampled economies in ASEAN financial stability reports during the post-COVID period further support the case for economy-specific scenario calibration within a regionally coordinated stress testing programme. Greater transparency in the disclosure of ASEAN bank stress test results particularly in the Philippines and Brunei, where disclosure frameworks remain less institutionally developed than in Malaysia and Indonesia would enhance the capacity of market participants to differentiate between resilient and vulnerable institutions and improve the allocational efficiency of capital flows within the ASEAN financial system.

CONCLUSION

This study examines the role of stress testing in reducing banking opacity and strengthening financial resilience within ASEAN's dual banking system, using a PVAR approach on a panel of 72 Islamic and conventional banks across five countries from 2012 to 2022. It represents the first application of this framework in a comparative conventional and Islamic banking context in ASEAN. The findings show that stress testing significantly influences credit risk dynamics in both banking systems. Macroeconomic and bank-specific variables function effectively as early warning indicators, providing meaningful insights into credit risk exposure and the underlying financial condition of banks, thereby enhancing transparency. The comparative results indicate no significant difference in the immediate credit risk response between Islamic and conventional banks under extreme shocks. However, differences arise in the adjustment dynamics over time, particularly in response to real interest rate shocks and the persistence of internal shocks, reflecting differences in financial structures and risk-sharing mechanisms. Policy implications include the need for differentiated stress testing frameworks tailored to each banking model, improved transparency in stress test disclosures, and the importance of maintaining disclosure standards to avoid masking underlying credit risks, as observed during the COVID-19 period. The study is limited by the small sample size of Islamic banks in certain countries. Future research should expand country coverage and incorporate additional risk factors such as exchange rate exposure, cross-border linkages, and digital banking competition.

REFERENCES

Abad, P., Robles, M.-D., & Alonso Orts, C. (2023). Stress testing programs and credit risk opacity of banks: USA vs Europe. Journal of International Financial Markets, Institutions and Money, 89, Article 101876. https://doi.org/10.1016/j.intfin.2023.101876

Abdeljawad, I., Rashid, M., Abu Alia, M., Qushtom, R., Irshaid, M., & Sahyouni, A. (2024). Cushion hypothesis and credit risk: Islamic versus conventional banks from the MENA region. PLOS ONE, 19(7), Article e0306901. https://doi.org/10.1371/journal.pone.0306901

Abdymomunov, A., & Gerlach, J. (2014). Stress testing interest rate risk exposure. Journal of Banking & Finance, 49, 287–301. https://doi.org/10.1016/j.jbankfin.2014.08.013

Abid, L., Ouertani, M. N., & Zouari-Ghorbel, S. (2014). Macroeconomic and bank-specific determinants of household's non-performing loans in Tunisia: A dynamic panel data approach. Procedia Economics and Finance, 13, 58–68. https://doi.org/10.1016/S2212-5671(14)00430-4

Abrigo, M. R. M., & Love, I. (2016). Estimation of panel vector autoregression in Stata. The Stata Journal, 16(3), 778–804. https://doi.org/10.1177/1536867X1601600314

Andrews, D. W. K., & Lu, B. (2001). Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. Journal of Econometrics, 101(1), 123–164. https://doi.org/10.1016/S0304-4076(00)00077-4

Basel Committee on Banking Supervision. (2009). Principles for sound stress testing practices and supervision (BCBS Working Paper No. 155). Bank for International Settlements. https://www.bis.org/publ/bcbs155.pdf

Blau, B. M., Brough, T. J., & Griffith, T. G. (2017). Bank opacity and the efficiency of stock prices. Journal of Banking & Finance, 76, 32–47. https://doi.org/10.1016/j.jbankfin.2016.11.026

Buston, C. S. (2015). Active risk management and banking stability. Journal of Banking & Finance, 79, 1–14. https://doi.org/10.1016/j.jbankfin.2015.01.016

Castro, V. (2013). Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI. Economic Modelling, 31, 672–683. https://doi.org/10.1016/j.econmod.2013.01.027

Chaibi, H., & Ftiti, Z. (2015). Credit risk determinants: Evidence from a cross-country study. Research in International Business and Finance, 33, 1–16. https://doi.org/10.1016/j.ribaf.2014.06.001

Daoud, Y., & Kammoun, A. (2024). Banking regulation and financial soundness nexus in view of the crisis: An Islamic banking perspective. International Journal of Economics and Financial Issues, 14(2), 113–122. https://doi.org/10.32479/ijefi.15760

De Mendonça, H. F., Galvão, D. J. C., & Loures, R. F. V. (2013). Credit and bank opaqueness: How to avoid financial crises? Economic Modelling, 33, 605–612. https://doi.org/10.1016/j.econmod.2013.05.001

Firdaus, N. A., Fakhruddin, I., Riyaldi, R., & Rosman, R. (2024). Liquidity and credit risk: A comparative study of Islamic and conventional banks in Indonesia. FINANSIA: Jurnal Akuntansi dan Perbankan Syariah, 7(1), 103–116. https://doi.org/10.32332/finansia.v7i1.8918

Flannery, M. J., Kwan, S. H., & Nimalendran, M. (2013). The 2007–2009 financial crisis and bank opaqueness. Journal of Financial Intermediation, 22(1), 55–84. https://doi.org/10.1016/j.jfi.2012.08.001

Flannery, M., Hirtle, B., & Kovner, A. (2017). Evaluating the information in the federal reserve stress tests. Journal of Financial Intermediation, 29, 1–18. https://doi.org/10.1016/j.jfi.2016.08.001

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. Journal of Econometrics, 115(1), 53–74. https://doi.org/10.1016/S0304-4076(03)00092-7

Khammassi, I., Boufateh, T., & Naoui, K. (2020). Do stress tests reduce liquidity risk opacity? American Journal of Finance and Accounting, 6(2), 135–158. https://doi.org/10.1504/AJFA.2020.110322

Khammassi, I., Boufateh, T., Naoui, K., Alrawad, M., & Lutfi, A. (2024). The role of stress tests in enhancing bank transparency: A comparative study of Islamic and conventional banks. ECONOMICS – Innovative and Economics Research Journal, 12(1), 71–100. https://doi.org/10.2478/eoik-2024-0003

Khan, M. F., Ali, M. S., Hossain, M. N., & Bairagi, M. (2023). Determinants of non-performing loans in conventional and Islamic banks: Emerging market evidence. Modern Finance, 1(1), 56–69. https://doi.org/10.61351/mf.v1i1.27

Kok, C., Müller, C., Ongena, S., & Pancaro, C. (2023). The disciplining effect of supervisory scrutiny in the EU-wide stress test. Journal of Financial Intermediation, 53, Article 101015. https://doi.org/10.1016/j.jfi.2022.101015

Levin, A., Lin, C. F., & Chu, C. S. J. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. Journal of Econometrics, 108(1), 1–24. https://doi.org/10.1016/S0304-4076(01)00098-7

Louzis, D. P., Vouldis, A. T., & Metaxas, V. L. (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business, and consumer loan portfolios. Journal of Banking & Finance, 36(4), 1012–1027. https://doi.org/10.1016/j.jbankfin.2011.10.012

Makri, V., Tsagkanos, A., & Bellas, A. (2014). Determinants of non-performing loans: The case of Eurozone. Panoeconomicus, 61(2), 193–206. https://doi.org/10.2298/PAN1402193M

Mishkin, F. S. (1999). Global financial instability: Framework, events, issues. Journal of Economic Perspectives, 13(4), 3–20. https://doi.org/10.1257/jep.13.4.3

Misman, F. N., & Bhatti, M. I. (2020). The determinants of credit risk: An evidence from ASEAN and GCC Islamic banks. Journal of Risk and Financial Management, 13(5), Article 89. https://doi.org/10.3390/jrfm13050089

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. Journal of Financial Economics, 13(2), 187–221. https://doi.org/10.1016/0304-405X(84)90023-0

Petrella, G., & Resti, A. (2013). Supervisors as information producers: Do stress tests reduce bank opaqueness? Journal of Banking & Finance, 37(12), 5406–5420. https://doi.org/10.1016/j.jbankfin.2013.01.005

Rohadi, S. C., Sarumpaet, S., & Syaipudin, U. (2024). Determinants of non-performing loans in ASEAN banking. Owner: Riset dan Jurnal Akuntansi, 8(2), 1917–1929. https://doi.org/10.33395/owner.v8i2.2331

Salas, M. B., Lamothe, P., Delgado, E., Fernández-Miguélez, A. L., & Valcarce, L. (2024). Determinants of nonperforming loans: A global data analysis. Computational Economics, 64(5), 2695–2716. https://doi.org/10.1007/s10614-023-10543-8

Salas, V., & Saurina, J. (2002). Credit risk in two institutional regimes: Spanish commercial and savings banks. Journal of Financial Services Research, 22(3), 203–224. https://doi.org/10.1023/A:1019781109676

Šeho, M., Bacha, O. I., & Smolo, E. (2024). Bank financing diversification, market structure, and stability in a dual-banking system. Pacific-Basin Finance Journal, 86, 102461. https://doi.org/10.1016/j.pacfin.2024.102461

Shank, C. A., & Vianna, A. C. (2016). Are US-dollar-hedged-ETF investors aggressive on exchange rates? A panel VAR approach. Research in International Business and Finance, 38, 430–438. https://doi.org/10.1016/j.ribaf.2016.05.002