

THE ROLE OF STRESS TESTS IN ENHANCING BANK TRANSPARENCY: A COMPARATIVE STUDY OF ISLAMIC AND CONVENTIONAL BANKS

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Received 20.11.2023.

Sent to review 30.11.2023.

Accepted 05.04.2024.

Original article



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JEL Classification: G21, C22, D81,
G32, G14

Doi: 10.2478/eoik-2024-0003

UDK: 336.763:338.124.4(28))

ABSTRACT

The global financial crisis highlighted the crucial role of stress tests in evaluating a bank's resilience to severe economic shocks. Accordingly, the purpose of the study was to examine the contribution of stress tests to credit risk in terms of hedging banking opacity and improving financial resistance against negative shocks in MENA countries, observed for the period from 2012 to 2022. Furthermore, this study explores the impact of stress tests on enhancing bank transparency, particularly within the contexts of Islamic and conventional banking systems using the Panel-VAR and GMM approach. A conceptual framework is established to explain the connection between stress testing and bank transparency, emphasizing on the mechanisms through which stress tests can promote greater disclosure and accountability. A comparative analysis of stress testing practices across both banking sectors reveals similarities and distinctions in scenario selection, modeling techniques, and disclosure practices. In-depth case studies of Islamic and conventional banks illustrate the practical application of stress testing in fostering transparency. These results show that stress tests produce information about credit risk exposure and about the real conditions of financial institutions. Therefore, more transparency on bank losses and risks would have also enabled bank regulators to focus more attention on financial institutions and react early to take "corrective measures". Policy recommendations are drawn to enhance the effectiveness of stress testing in promoting transparency and financial stability within both Islamic and conventional banking sectors. This study contributes to a deeper understanding of stress testing's role in fostering a more resilient and stable financial system.

Keywords: Stress tests, Panel-VAR, credit risk, Islamic banking, macroeconomic and specific shocks, financial stability

1. INTRODUCTION

The real concern of current research is to gather relevant information to understand better the risks faced by individual banks and thereof to shape regulation to strengthen the financial stability of the banking system (Buston, 2015). In fact, Mishkin (1999) pointed out that an increase in information asymmetry problems and financial instability is mainly due to the following factors: higher interest rates, greater uncertainty, and deterioration of non-financial balance sheets as a result of changes in asset prices. For example, Myers and Majluf (1984) argue that in

the face of asymmetrical information, shareholders make inefficient investment decisions that generate risky securities that are not properly valued in the marketplace. Flannery et al. (2013) revealed that banking opacity could be destabilizing when the financial system is under stress. Accordingly, Blau et al. (2017) argue that banks are more opaque than other types of firms.

Thus, studying the source of banking opacity is vital for strengthening financial resilience. On the other hand, increased banking transparency promotes the development of a sound banking system and an enabling environment, which facilitates the strengthening of the credit chain and avoids financial crises (De Mendonça et al, 2013). According to FCIR (2011), one of the root causes of the crisis is credit risk. Loans set interest rates for the first two or three years, then were subject to adjustable rates, and as a result borrowers defaulted. However, the rise in loan-to-value ratios due to the facility of credit flows has led to mediocre credit standards. With the large accumulation of mortgages and other high-risk mortgages in the financial system, it seems that many people with limited ability to pay have received high-risk mortgages with fraudulent practices from money lenders.

These mortgages were issued to borrowers who had lower credit rating and whose loan-to value ratio was higher. Indeed, they have less collateral, and have a more or less worse credit history. This subprime market increased significantly from 2003 until 2005. The proportion of subprime mortgages (i.e., total subprime mortgages) as a share of the total U.S. mortgage market has been increasing between 10% in 2003 and 32% in 2005 (Mayer et al, 2009). Therefore, the opacity of the interest rate risk and borrowers' insolvency risk has created a bank credit risk. According to Chakrabarti (2015), credit risk may be defined as a client's inability to repay interest or principal or both at the same time.

The credit quality of lending portfolios in most regions of the world was relatively stable until the 2007-2008 financial crisis. For this reason, the assessment and in-depth understanding of asset quality and credit risk in the financial sector has become an important component of supervision oversight, that facilitates the identification of major vulnerabilities in the financial sector (Roland et al. 2013). However, the financial crisis and its diffusion through the entire financial system has recently questioned the effectiveness of the risk management model and its ability to manage unexpected events and avoid future crises (Jawadi and Louhichi, 2017). In response to the crisis and as part of the second pillar 2 of Basel II, the Basel Committee suggests stress tests as a prudential supervisory tool, where banks are required to consider more severe scenarios in order to produce results that are more in line with the real constraints observed in BCBS (2009). As a result, the purpose of disclosing financial information to the public is to restore trust and reduce banking opacity by helping investors distinguish between sound and vulnerable institutions (Petrella and Resti, 2013). However, to evaluate the contribution of stress tests to credit risk in terms of hedging banking opacity in MENA countries, we will examine credit risk resistance against macroeconomic and specific shocks in order to examine the contribution of stress tests to reducing banking opacity by means of measuring the resistance of the studied banks. Studying both types of banks (Islamic and conventionnel) allows policymakers and researchers to grasp the contributions of each system in promoting inclusion. This understanding is vital, in evaluating how effectively each model reaches segments of the population including individuals, with ethical preferences.

To that end, we examine a panel data consisting of 72 listed banks in 7 MENA countries observed over an eleven-year period from 2012 to 2022. Our procedure is as follows: First, we examine previous studies on the contribution of stress tests to reducing banking opacity and improving financial resilience. Second, we will review the literature on determining credit risk to better understand the relationship between the variables in our model.

According to [Matthew et al \(2004\)](#), “Stress testing” in each financial institution is a set of techniques designed to measure the sensitivity of a portfolio to a set of extreme but plausible shocks. Simply put, when there are significant changes in some risk factors, stress tests produce a numerical estimate of a particular sensitivity. For this reason, we adopt the VAR Panel approach and the Generalized Method of Moments (GMM). Concomitantly, we follow [Abrigo and Love \(2015\)](#) and examine credit risk responses to specific and macroeconomic shocks. For this latter analysis, we impulse response functions (IRFs) and variance decomposition (FEVD), which describes the reaction of one variable on another variable to adverse events, while maintaining all other shocks at zero. The premise on which this methodology rests is to identify a series of shocks and to determine the effect of these shocks as well as the instantaneous or long-term responses of some variables to certain impulses. The PVAR is an hybrid econometric methodology that combines the traditional VAR approach, which considers all structural variables as endogenous, and the Panel data methodology, which makes it possible to explicitly include a fixed effect estimate in the model ([Shank and Vianna, 2016](#)).

The remainder of the article is organized as follows. Section 2 provides a brief review of the contribution of stress tests to reducing banking opacity and to improving resistance of financial institutions to extreme shocks. Section 3 provides an overview of the data and defines the variables used and describes the methodology employed. Section 4 discusses the results obtained. Section 5 concludes.

2. LITERATURE REVIEW

In this section, we review the literature on the contribution of stress tests to reducing banking opacity and strengthening financial stability. Generally, banks that frequently hide negative information increase the probability of future shocks through the information asymmetry factor ([Kosmidou et al, 2016](#)). Indeed, [Flannery et al. \(2016\)](#) suggest that disclosure of stress test results systematically provides important information about the tested banks. Accordingly, the purpose of disclosing the results on financial resistance to the public is to restore trust and reduce banking opacity by helping investors distinguish between sound and vulnerable institutions [Petrella and Resti \(2013\)](#).

[Kok et al. \(2023\)](#) investigate how stress testing can lower risk by taking advantage of variations in stress test intensity at the bank level. They use quarterly bank-level data for the period between 2015Q1 and 2017Q4 from the European Central Bank’s confidential Supervisory Banking (SUBA) database¹⁷. They find that stress tests have the potential to influence bank risk rather than just being a regulatory checkbox exercise. They discover that, in comparison to banks that were not involved in this exercise, banks that took part in the 2016 EU-wide stress test later decreased their credit risk.

This study of [Abad el al. \(2023\)](#) investigate whether the opacity of data regarding banks’ credit risk has decreased as a result of stress tests that were carried out in the US and the EU between 2009 and 2019. The original sample consisting of 540 American and 266 European banks. To investigate the factors influencing the shift in the opacity level after the disclosure, we constructed a panel data model.

After the disclosure, there is clear evidence of a decrease in the opacity of banks evaluated in the US ST; this reduction is more pronounced for banks that fail to pass the test. These findings lend support to the hypothesis that the ST programs, particularly for banks that fail to pass the test, mitigate the opacity of the US banking industry. According to data, the transparency of the banking system in Europe does not appear to have improved with the release of the ST results.

Due to its complexity, there is little proof that the information generated by the EBA programs has an impact on the information opacity of the banking sector and may not be sufficiently transparent or accessible to subjective interpretations.

Khammassi et al. (2020) examine the contribution of stress tests to reducing banking opacity and ensuring the financial resilience of liquidity risk in the face of adverse shocks. The sample includes 74 listed banks in 7 MENA countries, during the 2005–2015 period. used the generalized method of moments (GMM) to conduct two estimations of the panel-VAR approach. We concluded that stress tests could play a fundamental role in reducing banking opacity by producing relevant information about banks' risk exposure, their current circumstances and their ability to resist adverse events.

Abdymomunov and Gerlach (2014) proposed a new method for generating scenario curves to test the stress of banks' IRR exposure, using the **Nelson-Siegel (1987)** (NS) yield curve model. The data are zero-coupon Treasury interest rates at month-end at maturities of 1, 3, 6, 12, 24, 36, 60, 84, 120, 240, and 360 months. The data are obtained from three sources. The study period stretches from 1985: M11 to 2012: M12. The results indicate that their scenario generation method produces a wider range of EVE estimates than alternative methods do. They noted out that, in comparison to previous methods, their method offers more information about IRR exposure.

Petrella and Resti (2013) assessed whether and how the 2011 European stress test can affect the stock price of banks. They selected 201 banks from the Thomson Reuters European Banks index (LBANKSER), representing more than 75% of the European banking sector in market capitalization. They followed standard event study techniques (**Campbell et al. 1997**) using cumulative abnormal returns. The model is estimated over a 200-day window. The results of these stress tests have been recently released to the public and led to the construction of 3400 data points for each of the 90 participating banks in an attempt to restore trust and combat banking opacity, making it easier for investors to distinguish between strong and fragile institutions.

At the time of the results, the market reacted significantly to the disclosure of the detailed resistance test results. **Petrella and Resti (2013)** found that the tested banks showed a positive reaction during the (-2, +2) window, while the untested banks experienced negative abnormal returns. The difference between the two groups is statistically significant and this means that the stress tests revealed new information about the tested banks. This confirms that the market is not able to anticipate the results of the tests.

In fact, the effect of stress tests on opacity and bank risk premiums depends on the type of available data in the market when the results are published. **Goldstein and Sapra (2012)** suggest that detailed disclosure is preferable to aggregate disclosure (such as aggregate capital deficiency) Also recognize that the benefit of disclosure of stress test results are that they enhance financial stability.

Using a theoretical model, **Gick and Pausch (2012)** demonstrate how a banking authority can commit to disclose the results of stress testing in order to effectively regulate the banking industry. This is achieved through a disclosure scheme where supervisors disclose information about the methodology (e.g., the signal generation process) and the results of stress tests (the signal). In general, they conclude that stress tests create value by improving information disclosure between the supervisor and investors.

Ellahie (2012) also studied the 2011 European stress test in order to determine whether results disclosure influences the information asymmetry. It uses bid-ask spreads for equity, spreads for credit instruments, and implied volatility of equity options as a measure of information asym-

metry. It examined the stress tests of 78 European banks selected in 2009, 2010 and 2011. As a methodology, the author uses the Difference In Difference (DID) technique, where the effect of stress tests on bid-ask spreads and volatility is implicit. The author concluded that stress tests did not correlate with a significant decrease in information asymmetry.

However, We can draw the conclusion that stress testing give market participants useful information and can help minimize banking opacity. This finding confirms the informational role of stress tests, which is consistent with the hypothesis that stress tests contribute to reducing banking opacity.

3. METHODOLOGY AND DATA

To provide answers on the ability of stress tests to reduce banking opacity, this paper aims to study credit risk resistance of the studied banks against specific and macroeconomic shocks.

3. 1. EMPIRICAL METHODOLOGY

We use the VAR Panel approach to study credit risk response to specific and macroeconomic shocks. The idea on which this methodology rests is to identify a series of shocks and to determine the effect of these shocks as well as the instantaneous or long-term responses of some variables to certain impulses. The advantage of P-VAR is its ability to simulate portfolio-level loss distributions in subsequent years for financial institutions. We try to test the credit risk stress of a set of banks in the MENA banking system against macroeconomic and specific shocks using the Panel-VAR and the Generalized Method of Moments (GMM), like in [Abrigo and Love \(2015\)](#). The frequency is yearly, and the establishment and estimation of PVAR model is completed in the STATA 13 software.

We estimate the following equation to present the retained variables:

$$Y_{it} = Y_{it-1}A_1 + Y_{it-2}A_2 + \dots + Y_{it-p+1}A_p + X_{it}B + \mu_{it} + e_{it} \quad (1)$$

$$i \in \{1, 2, \dots, N\}, t \in \{1, 2, \dots, T_i\}$$

Where Y_{it} is a variable vector ($NPLs_{it}$, RIR_{it} , INF_{it} , GDP_{it} , $SIZE_{it}$, CAP_{it}) of bank i at time t . X_{it} represents exogenous variable vector, $A_1, A_2, \dots, A_p$ and B are vectors to be estimated

T is the year period ($t=2012-2022$), i denotes banks, μ_{it} and e_{it} represent random error term.

$NPLs_{it}$: Credit risk is measured by the non-performing loans ratio, CAP_{it} : The solvency ratio, $SIZE_{it}$: Bank size, RIR_{it} : The real interest, INF_{it} : Rate inflation rate, GDP_{it} : GDP growth rate.

We estimate PVAR presented in (1) using ordinary least squares (OLS) refer to [Abrigo and Love \(2015\)](#).

3. 2. DATA DESCRIPTION

The full sample spans 11 year (2012-2022) and comprises 48 conventional banks and 24 islamic banks from 7 MENA countries.

A. Credit risk (Npls)

Assessment and in-depth understanding of credit risk in the financial sector has become an vital component of prudential supervision, which enables the identification of key vulnerabilities in the financial sector [Roland et al. \(2013\)](#).

Credit risk: Credit risk is the possibility of loss that a lender may experience as a result of a

debtor's failure to make contractual payments or as a result of an increase in the probability of the debtor's default as a result of downgrading as credit risk, Küçükkoçaoğlu (2016).

NPLs ratio is a measure of credit risk. Accordingly, NPL as defined in Mpofu. T.R and Nikolaidou. E (2018), is equal to the following:

$$\text{NPLs} = \left(\frac{\text{non-performing loans}}{\text{total loan}} \right)_{i,t} \quad (2)$$

B. Solvency

Solvency: Kingu et al. (2018) use this variable as an example of a representative type of financial risk indicator and capital adequacy ratio for banks. we measure solvency in the same manner as Psaila et al. (2019)

$$\text{Solvency} = \left(\frac{\text{Equity}}{\text{total assets}} \right)_{i,t} \quad (3)$$

Makri et al. (2014), and Chaibi and Ftiti (2015) suggest that managers of small-cap banks are encouraged to engage in risky lending practices, As a result, there is a negative correlation between NPLs and “solvency ratio.”

C. Bank Size

Bank Size: The natural logarithm of the total banking assets is used to calculate the size of the bank, which is considered the most popular measure of bank size in banking literature Rahman et al (2012). Thus, we calculate the size of the bank using the formula: Bank size =Log (total assets). According to Louzis, D. et al. (2012), SIZE has an adverse effect on asset quality. When banks grow too big, monitoring and evaluating them becomes challenging because they take on more risk and may become “too big to fail.”. Salsa and Saurina (2002) discovered a correlation between bank size and NPL that was negative.; they showed that a larger bank size allows for greater diversification, leading to an increase in non-performing loans. The NPL is negatively and significantly impacted by the bank's size (Singh et al., 2021).

D. Real interest rate

The borrowing rate also increasingly affects non-performing loans. Therefore, the government must create laws that will lower borrowing costs in the National Economy (Akinlo, 2014) The Real Lending Ratio (RLR) coefficients are positive. Therefore, households' NPLs are sensitive to changes in RLR (Abid et al., 2014).

E. Inflation rate

Economic stability, which promotes saving, investment, economic growth, and aids in maintaining global competitiveness, is made possible by low inflation. So, low inflation is a positive sign for economic growth. High inflation decreases the borrower's ability to pay off its loan by lowering its income, which raises the NPL, according to Singh et al. (2021). The inflation rate has a considerable positive impact on NPLs, according to Louzis et al. (2010), who used a dynamic panel data model to study the determinants of NPL in the Greek banking industry. Additionally, Ghosh (2015) examined the impact of NPLs on US commercial banks and discovered that inflation had a significant and positive impact on questionable loans.

F. GDP growth

GDP is an economic indicator. In fact, to evaluate an economic growth of the country, we use

the GDP growth rate shown in equation 3 (Singh et al., 2021).

$$\text{GDP growth} = \frac{\text{GDP}_{i,t} - \text{GDP}_{i,t-1}}{\text{GDP}_{i,t}} \quad (4)$$

According to Castro (2013) and Chaibi and Ftiti (2015), the Real GDP growth rate and non-performing have a negative correlation. Louzis et al. (2010) investigated the factors that influence non-performing loans in the Greek financial industry using a dynamic panel data model, and they discovered that the real GDP growth rate had a negative impact on NPLs. Vogiazes and Nikolaidu (2011) investigated the factors that contributed to non-performing loans in the banking industry of Romania between 2001 and 2010. They showed that among the major determinants of non-performing loans in Romania are the rate of inflation the GDP.

However, Bofondi and Ropele (2011) discovered a negative correlation between non-performing loans and Italy's GDP growth rate between 1990 and 2010. The NPL of commercial banks is positively and significantly impacted by GDP growth, Singh et al. (2021). Roland et al. (2013) observed a negative impact of real GDP on NPLs. As well, Abid et al. (2015) found that real GDP negatively impacts NPLs (e.g. Khaled and Yusof, 2024).

3. 3. PANEL UNIT ROOT TESTS

The following table shows the outcomes of the several stationarity tests: We start by checking the stationarity of the variables. The results of the unit root tests of Levin, Lin and Chu; Im, Pesaran; Shin, ADF - Fisher Chi-square and PP - Fisher Chi-square indicate that the GDP, SIZE, CAP series are stationary in level and the NPLs, INF and RIR series are non-stationary, or order (1) integrated (see Table 1). As a result, we estimate the model using the first difference between the variables.

Table 1. Stationarity of conventional banks

			NPLs	INF	GDP	SIZE	CAP	RIR
LLC	NIV	cst	-8.49611 (0.0000)	-5.703 (0.0000)	-6.53155 (0.0000)	-17.3368 (0.0000)	-9.15486 (0.0000)	-12.1140 (0.0000)
		cst & tend	-0.81601 (0.2072)	-7.59718 (0.0000)	176.649 (0.0000)	-23.1230 (0.0000)	-21.3281 (0.0000)	-10.5699 (0.0000)
	1 ^{ère} diff	cst	-6.28271 (0.0000)	-20.59 (0.0000)	-22.66 (0.0000)	-25.64 (0.0000)	-21.9153 (0.0000)	-35.0250 (0.0000)
		cst & tend	-5.86260 (0.0000)	-19.1579 (0.0000)	281.564 (0.0000)	-22.39 (0.0000)	-18.53 (0.0000)	-37.5401 (0.0000)
IPS	NIV	cst	-3.08532 (0.0010)	-3.469 (0.0003)	-3.055 (0.0011)	-8.6977 (0.0000)	-4.19407 (0.0000)	-7.32749 (0.0000)
		cst & tend	1.83209 (0.9665)	0.02778 (0.5111)	158.578 (0.0001)	-7.49844 (0.0000)	-5.44084 (0.0000)	-2.38950 (0.0084)
	1 ^{ère} diff	cst	-6.06542 (0.0000)	-9.872 (0.0000)	-12.3882 (0.0000)	-12.08 (0.0000)	-11.0574 (0.0000)	-22.4969 (0.0000)
		cst & tend	-1.79104 (0.0366)	-2.91938 (0.0018)	193.023 (0.0000)	-4.19945 (0.0000)	-4.16817 (0.0000)	-11.7015 (0.0000)
ADF	NIV	cst	146.973 (0.0006)	130.80 (0.0105)	130.498 (0.0111)	251.222 (0.0000)	175.640 (0.0000)	214.749 (0.0000)
		cst & tend	123.226 (0.0320)	77.6419 (0.9149)	-3.17750 (0.0007)	259.517 (0.0000)	212.249 (0.0000)	166.523 (0.0000)
	1 ^{ère} diff	cst	267.713 (0.0000)	278.202 (0.0000)	336.153 (0.0000)	313.050 (0.0000)	302.09 (0.0000)	538.241 (0.0000)
		cst & tend	185.072 (0.0000)	170.036 (0.0000)	-3.20382 (0.0007)	223.29 (0.0000)	220.16 (0.0000)	425.562 (0.0000)
PP	NIV	cst	127.533 (0.0173)	129.502 (0.0129)	120.992 (0.0432)	393.925 (0.0000)	199.940 (0.0000)	190.619 (0.0000)
		cst & tend	89.7694 (0.6596)	130.830 (0.0105)	-13.8593 (0.0000)	242.81 (0.0000)	220.326 (0.0000)	282.938 (0.0000)
	1 ^{ère} diff	cst	268.381 (0.0000)	333.340 (0.0000)	404.980 (0.0000)	266.275 (0.0000)	339.19 (0.0000)	668.660 (0.0000)
		cst & tend	264.836 (0.0000)	291.29 (0.0000)	-18.3138 (0.0000)	223.505 (0.0000)	288.258 (0.0000)	677.479 (0.0000)

NB: If the p-value (values in brackets) are less than 0.01 ; 0.05 ; 0.10 it means that the variables are stationary at the 1%; 5% ; 10% levels respectively.

Source: Primary data analysis output

By performing the stationarity test of Levin, Lin and Chu; Im, Pesaran; Shin, ADF - Fisher Chi-square and PP - Fisher Chi-square, we found that GDP, SIZE and CAP series are stationary in level, while the NPLs, INF and RIR series are non-stationary or order (1) integrated (see Table 2).

Table 2. Stationarity of Islamic banks

			NPLs	INF	GDP	SIZE	CAP	RIR
LLC	NIV	cst	-8.9484 (0.0000)	-5.1307 (0.0000)	-7.23778 (0.0000)	-13.9106 (0.0000)	-28.93 (0.0000)	-8.01045 (0.0000)
		cst & tend	-13.2940 (0.0000)	-6.50634 (0.0000)	-12.0283 (0.0000)	-11.90 (0.0000)	-10.91 (0.0000)	-4.77657 (0.0000)
	1 ^{ère} diff	cst	-15.3577 (0.0000)	-14.8351 (0.0000)	-18.203 (0.0000)	-12.8164 (0.0000)	-14.613 (0.0000)	-20.7179 (0.0000)
		cst & tend	-147.594 (0.0000)	-13.3603 (0.0000)	-14.578 (0.0000)	-43.6844 (0.0000)	-720.556 (0.0000)	-22.8978 (0.0000)
IPS	NIV	cst	-3.55922 (0.0002)	-2.54724 (0.0054)	-3.12823 (0.0009)	-6.39109 (0.0000)	-8.5300 (0.0000)	-4.16185 (0.0000)
		cst & tend	-0.81431 (0.2077)	-0.1334 (0.4469)	-2.92672 (0.0017)	-1.71716 (0.0430)	-1.831 (0.0335)	-0.47023 (0.3191)
	1 ^{ère} diff	cst	-6.35110 (0.0000)	-7.134 (0.0000)	-9.7030 (0.0000)	-5.13071 (0.0000)	-8.780 (0.0000)	-13.1209 (0.0000)
		cst & tend	-3.76194 (0.0001)	-1.96194 (0.0249)	-2.51056 (0.0060)	-4.60207 (0.0000)	-4.1089 (0.0000)	-6.35789 (0.0000)
ADF	NIV	cst	82.5497 (0.0008)	68.141 (0.0449)	78.3261 (0.0064)	114.85 (0.0000)	122.67 (0.0000)	93.6683 (0.0002)
		cst & tend	60.1825 (0.0211)	42.693 (0.7587)	90.3533 (0.0004)	83.632 (0.0003)	79.537 (0.0008)	60.2988 (0.1510)
	1 ^{ère} diff	cst	104.178 (0.0000)	145.07 (0.0000)	189.211 (0.0000)	111.69 (0.0000)	169.27 (0.0000)	238.350 (0.0000)
		cst & tend	83.6627 (0.0000)	86.0596 (0.0012)	108.164 (0.0000)	108.67 (0.0000)	135.44 (0.0000)	179.065 (0.0000)
PP	NIV	cst	86.6674 (0.0003)	67.5643 (0.0495)	69.9399 (0.0327)	214.407 (0.0000)	129.82 (0.0000)	86.5632 (0.0010)
		cst & tend	78.621 (0.0003)	65.065 (0.0746)	107.465 (0.0000)	115.71 (0.0000)	142.18 (0.0000)	104.227 (0.0000)
	1 ^{ère} diff	cst	118.65 (0.0000)	191.78 (0.0000)	244.048 (0.0000)	119.453 (0.0000)	229.485 (0.0000)	326.717 (0.0000)
		cst & tend	129.974 (0.0000)	165.37 (0.0000)	172.243 (0.0000)	153.23 (0.0000)	230.599 (0.0000)	313.697 (0.0000)

Source: Primary data analysis output

3. 4. DESCRIPTIVE STATISTICS

Before presenting our econometric estimates, a descriptive analysis of credit risk and its independent variables as shown in Table 3

Table 3. Descriptive statistics

	N	Mean	Median	Standard deviation	JB		Shap-iro-Wilk (w)	Shap-iro-Francia
					Skewness	Kurtosis		
Panel A: conventional banks								
NPLs	470	5.6107	3.185	7.3108	0.0000	0.0000	0.59435 (0.0000)	0.59160 (0.00001)
					(0.0000)			
INF	528	5.8120	4.6	4.52138	0.0000	0.4813	0.94380 (0.0000)	0.94330 (0.00001)
					(0.0000)			
GDP	528	4.9787	4.6	4.4837	0.0000	0.0000	0.85249 (0.0000)	0.85033 (0.00001)
					(0.0000)			
SIZE	494	3.9887	4.0211	0.5686	0.5408	0.0000	0.97070 (0.0000)	0.97251 (0.00001)
					(0.0000)			
RIR	528	2.6926	2	8.6305	0.0000	0.0000	0.70906 (0.0000)	0.70697 (0.00001)
					(0.0000)			
CAP	486	14.3605	13.3836	5.3733	0.0000	0.0000	0.78454 (0.0000)	0.78169 (0.00001)
					(0.0000)			
Panel B: Islamic banks								
NPLs	190	6.4723	4.125	7.5414	0.0000	0.0000	0.7125 (0.0000)	0.7101 (0.00001)
					(0.0000)			
INF	264	4.7591	3.3	4.1310	0.0000	0.0752	0.9044 (0.0000)	0.9033 (0.00001)
					(0.0000)			
GDP	264	5.0575	4.6	4.8172	0.0000	0.0000	0.8664 (0.0000)	0.8625 (0.00001)
					(0.0000)			
SIZE	226	3.8625	3.8481	0.4749	0.9174	0.1945	0.9928 (0.3408)	0.9937 (0.40153)
					(0.4252)			
RIR	264	3.0409	1	10.2579	0.0000	0.0000	0.7709 (0.0000)	0.7681 (0.00001)
					(0.0000)			
CAP	223	14.741	13.3150	7.9412	0.0000	0.0000	0.8977 (0.0000)	0.8957 (0.00001)
					(0.0000)			

Source: Primary data analysis output

Table 4 below presents the estimation of correlation between the various variables used in our econometric model. The findings of the correlation matrix for conventional bank variables indicate a strong link between credit risk and GDP, CAP, and SIZE. These factors have a bad relationship with this risk. However, there is no causal correlation between the other factors (RIR and INF) and credit risk as shown in table 4.

In a similar vein, the findings from the correlation matrix for Islamic bank factors demonstrate a high association to credit risk, with the exception of GDP and CAP. These factors, however, showed a negative relationship with credit risk, whereas there is no correlation with the other variables.

Table 4. Correlation statistics

Panel A conventional banks					
	NPLS	INF	GDP	SIZE	RIR
NPLS	1.0000				
INF	0.1514*	1.0000			
GDP	-0.1564*	0.1311*	1.0000		
SIZE	-0.3562*	-0.4030*	-0.0442	1.0000	
RIR	-0.0426	-0.2421*	-0.2576*	0.0956*	1.0000
CAP	-0.0814	-0.0983*	-0.0117	-0.1640*	-0.0332
Panel B : Islamic banks					
	NPLS	INF	GDP	SIZE	RIR
NPLS	1.0000				
INF	0.1317	1.0000			
GDP	-0.2007*	0.1699*	1.0000		
SIZE	-0.1056	-0.1525*	-0.1318*	1.0000	
RIR	-0.0340	-0.2464*	-0.3075*	0.0757	1.0000
CAP	-0.3773*	-0.1806*	0.3245*	-0.3068*	-0.0428

** significance at 5%

Source: Primary data analysis output

4. RESULTS AND DISCUSSION

Based on the three selection criteria of Andrews and Lu's (2001) models, such as MBIC, MAIC and MQIC, the "order-1" liquidity risk model for Islamic and conventional banks is the most stable model, since it has the smallest MBIC, MAIC and MQIC. (see **table 5**). Indeed, to protect against loss of degrees of freedom, we have chosen the "order-1" credit risk model for Islamic banks, because the theory sets an order of 1 for a small sample size.

Table 5. PVAR's optimal moment and model selection criteria

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	.9999991	161.8962	.0006112	-430.0128	-54.10383	-205.5677
2	.9999992	119.4896	.0003728	-275.1164	-24.51043	-125.4864
3	.9999144	51.39249	.046319	-145.9105	-20.60751	-71.09547

Source: Primary data analysis output

In **Table 6**, we report the coefficients of the PVAR model using the "GMM" method. We found a positive relationship between credit risk and its innovations, significant at the 5% level. We discovered a significant relationship at the 5% level between credit risk and solvency as well as a negative relationship between credit risk and real interest rate. This finding suggests that the credit risk of traditional banks is positively impacted by credit from the previous year, and negatively by the real interest rate and solvency.

Table 6. PVAR's estimates for conventional banks

	dNPLs	d INF	GDP	SIZE	RIR	CAP
d NPLs	0.0925676 (0.031)	-0.356801 (0.000)	-0.4874889 (0.000)	-0.003183 (0.000)	0.9695921 (0.000)	0.0586824 (0.000)
d INF	-0.041272 (0.195)	0.0379174 (0.152)	0.3751708 (0.000)	-0.0000333 (0.952)	-0.360798 (0.001)	0.0207276 (0.298)
GDP	-0.034989 (0.158)	-0.000050 (0.998)	0.1220883 (0.000)	-0.0002618 (0.527)	0.0275281 (0.726)	0.0107696 (0.432)
SIZE	-0.398547 (0.745)	-2.605846 (0.066)	-32.7261 (0.000)	0.9235336 (0.000)	80.20202 (0.000)	-2.328599 (0.011)
RIR	-0.044773 (0.001)	0.0806341 (0.000)	0.1437283 (0.000)	0.0003353 (0.164)	-0.149611 (0.004)	0.0138992 (0.088)
CAP	-0.219420 (0.007)	-0.164297 (0.007)	-0.7350125 (0.000)	0.0092982 (0.000)	0.0388805 (0.891)	0.475399 (0.000)

Source: Primary data analysis output

In **Table 7**, we report the coefficients of the PVAR model using the “GMM” method. During previous years, we saw a negative correlation between credit risk and credit risk, significant, between bank size and solvency, significant at the 5% level and between inflation rate and interest rate, significant at the 1% level. Indeed, we notice that the credit risk of Islamic banks is negatively affected by the credit risk of previous years, bank size, solvency, inflation rate and interest rate.

Table 7. PVAR's estimates for Islamic banks GMM

	dNPLs	dINF	GDP	SIZE	dRIR	CAP
dNPLs	-0.067164 (0.046)**	-0.029307 (0.000)***	-0.196895 (0.000)***	-0.0010937 (0.052)*	0.2469293 (0.000)***	0.1125992 (0.952)
dINF	-0.190557 (0.000)***	-0.153812 (0.000)***	-0.186142 (0.000)***	-0.0005815 (0.660)	1.115333 (0.000)***	-0.0137093 (0.521)
GDP	0.0129106 (0.617)	0.0536995 (0.000)	0.1216947 (0.000)	0.0018498 (0.010)	0.5218464 (0.000)	-0.0763905 (0.000)
SIZE	-4.035056 (0.026)**	4.687471 (0.000)***	-20.2557 (0.000)***	0.6877609 (0.000)***	91.91684 (0.000)***	5.72044 (0.000)***
dRIR	-0.027629 (0.000)***	-0.012518 (0.000)***	-0.040191 (0.000)***	0.0000262 (0.848)	-0.0955139 (0.000)***	-0.0107679 (0.027)**
CAP	-0.161501 (0.005)**	0.1382489 (0.000)***	-0.312514 (0.000)***	-0.0120595 (0.121)	1.13411 (0.000)***	1.109719 (0.000)***

Source: Primary data analysis output

Granger Wald's causality test results of the order-1 PVAR (**Table 8**) provide statistical evidence for the presence of a causal relationship between the variables. Indeed, we found that the causal relationship between interest rate and solvency are significant at the 5% level, i.e., interest rate and solvency explain the credit risk of conventional banks.

Table 8. PVAR's post-estimation tests for conventional banks

		chi2	df	Prob > chi2
d NPLs	d INF	1.679	1	(0.195)
	GDP	1.994	1	(0.158)
	SIZE	0.106	1	(0.745)
	RIR	10.309	1	(0.001)***
	CAP	7.354	1	(0.007)**
	All	50.591	5	(0.000)***
d INF	d NPLs	129.130	1	(0.000)
	GDP	0.000	1	(0.998)
	SIZE	3.381	1	(0.066)
	RIR	47.412	1	(0.000)
	CAP	7.176	1	(0.007)
	All	203.610	5	(0.000)
GDP	d NPLs	83.279	1	(0.000)
	d INF	48.750	1	(0.000)
	SIZE	214.679	1	(0.000)
	RIR	20.539	1	(0.000)
	CAP	40.649	1	(0.000)
	All	284.958	5	(0.000)
SIZE	d NPLs	40.275	1	(0.000)
	d INF	0.004	1	(0.952)
	GDP	0.401	1	(0.527)
	RIR	1.934	1	(0.164)
	CAP	65.381	1	(0.000)
	All	144.084	5	(0.000)
RIR	d NPLs	49.509	1	(0.000)
	d INF	11.259	1	(0.001)
	GDP	0.123	1	(0.726)
	SIZE	250.436	1	(0.000)
	CAP	0.019	1	(0.891)
	All	570.452	5	(0.000)
CAP	d NPLs	12.905	1	(0.000)
	d INF	1.082	1	(0.298)
	GDP	0.616	1	(0.432)
	SIZE	6.387	1	(0.011)
	RIR	2.902	1	(0.088)
	All	34.243	5	(0.000)
All the eigenvalues lie inside the unit circle.				
PVAR satisfies stability condition.				
Eigenvalue stability condition				
	Eigenvalue	Imaginary		Modulus
Real	.9270012	0		.9270012
	.4513925	0		.4513925
	-.0468805	-.1609306		.16762
	-.0468805	.1609306		.16762
	.108631	-.0425859		.1166801
	.108631	.0425859		.1166801

Source: Primary data analysis output

Table 8. PVAR's post-estimation tests Panel VAR-Granger causality Wald test

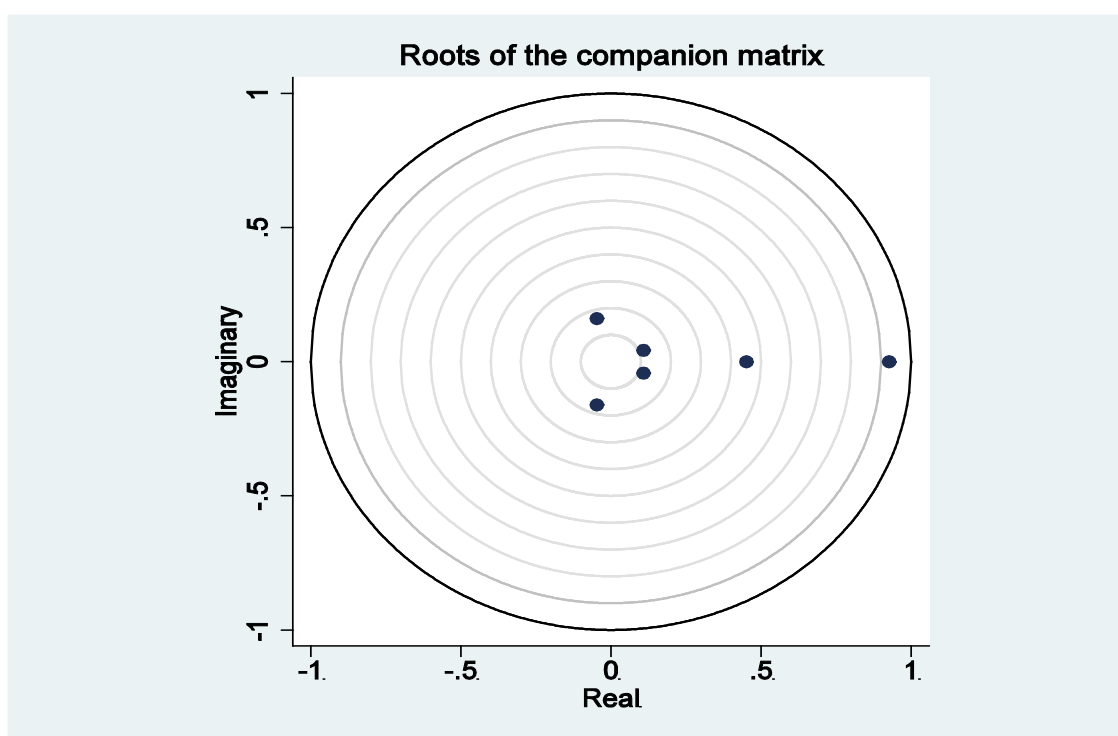
Ho: Excluded variable does not Granger-cause Equation variable

H1: Excluded variable Granger-causes Equation variable

The eigenvalues presented in table and figure 1 confirm that the PVAR model of credit risk for conventional banks is stable. The estimates are clearly less than 1. Thus, Figure No. 1 visually indicates that these eigenvalues are within the unity circle. Therefore, the stability condition of the VAR panel estimates is checked.

Figure 1 shows the eigenvalue stability condition of Non-performing loan ratio, inflation rate, GDP growth rate, bank size, real interest rate and solvency ratio for 48 conventional banks during 11 years from Bankscope and World Bank.

Figure 1. Eigenvalue in the unit circle for conventional banks



Source: Primary data analysis output

Figure 1 shows the eigenvalue stability condition of Non-performing loan ratio, inflation rate, GDP growth rate, bank size, real interest rate and solvency ratio for 48 conventional banks during 11 years from Bankscope and World Bank.

Granger Wald's causality test results of the order-1 PVAR (Table 9) provide statistical evidence for the presence of a causal relationship between the variables. In fact, we discovered that whereas bank size and solvency causal coefficients are significant at the 5% level, the causal coefficients of inflation rate and interest rate are significant at the 1% level. Indeed, inflation rate, interest rate, solvency and bank size explain the credit risk of Islamic banks.

Table 9. PVAR's post-estimation tests for islamic banks

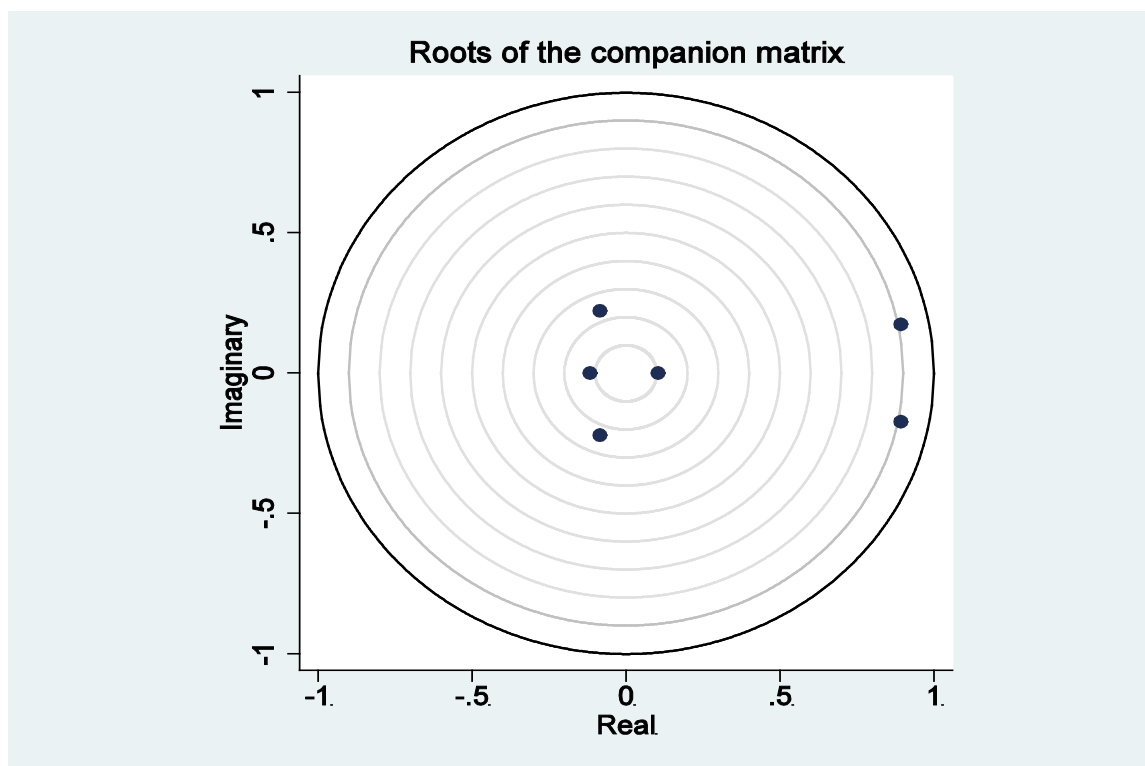
		chi2	df	Prob > chi2
d NPLs	d INF	45.083	1	(0.000)***
	GDP	0.250	1	(0.617)
	SIZE	4.929	1	(0.026)**
	dRIR	14.173	1	(0.000)***
	CAP	7.915	1	(0.005)**
	All	188.730	5	(0.000)***
d INF	d NPLs	14.511	1	(0.000)
	GDP	31.464	1	(0.000)
	SIZE	44.637	1	(0.000)
	dRIR	21.425	1	(0.000)
	CAP	12.759	1	(0.000)
	All	137.578	5	(0.000)
GDP	d NPLs	23.060	1	(0.000)
	d INF	20.225	1	(0.000)
	SIZE	241.943	1	(0.000)
	dRIR	17.370	1	(0.000)
	CAP	29.348	1	(0.000)
	All	632.944	5	(0.000)
SIZE	d NPLs	3.786	1	(0.052)
	d INF	0.194	1	(0.660)
	GDP	6.579	1	(0.010)
	dRIR	0.037	1	(0.848)
	CAP	2.401	1	(0.121)
	All	34.010	5	(0.000)
dRIR	d NPLs	12.981	1	(0.000)
	d INF	99.606	1	(0.000)
	GDP	41.932	1	(0.000)
	SIZE	360.656	1	(0.000)
	CAP	24.108	1	(0.000)
	All	1677.044	5	(0.000)
CAP	d NPLs	0.004	1	(0.952)
	d INF	0.412	1	(0.521)
	GDP	19.757	1	(0.000)
	SIZE	26.094	1	(0.000)
	dRIR	4.879	1	(0.027)
	All	57.818	5	(0.000)
All the eigenvalues lie inside the unit circle.				
PVAR satisfies stability condition.				
Eigenvalue stability condition				
Real	Eigenvalue	Imaginary		Modulus
	.8925202	.1734722		.9092221
	.8925202	-.1734722		.9092221
	-.084709	.2214848		.2371311
	-.084709	-.2214848		.2371311
	-.117027	0		.117027
	.1040885	0		.1040885

Source: Primary data analysis output

We use the variables: dnpls: Non-performing loan ratio. dinf: inflation rate. GDP : GDP growth rate. SIZE: bank size. RIR: real interest rate. CAP: solvency ratio.

The eigenvalues presented in table and figure 2 confirm that our VAR panel model of credit risk for Islamic banks is stable. The table shows that the estimates are clearly less than 1. Thus, Figure 2 visually indicates that these eigenvalues are within the unity circle. Therefore, the stability condition of the VAR panel estimates is checked.

Figure 2. Graph of eigenvalue in the unit circle for islamic banks



Source: Primary data analysis output

Figure 2 displays the liquidity risk eigenvalue stability condition, Non-performing loan ratio, inflation rate, GDP growth rate, bank size, real interest rate and for 24 islamic banks during 11 years from Bankscope and World Bank.

Looking into the results of variance decomposition (see **Table 10**), we notice that 97.21% of the change in conventional banks' credit risk is explained by itself, and only 0.94%, 0.86%, 0.78%, 0.14% and 0.04% of the change in credit risk is explained by solvency, bank size, real interest rate, GDP growth rate and inflation rate shocks, successively.

Table 10. FEVD: Forecast-error variance decomposition for conventional banks

Response variable And Fore-cast	horizon	dnpls Impulse	dinf	GDP	SIZE	RIR	CAP
dnpls	0	0	0	0	0	0	0
	1	1	0	0	0	0	0
	2	0.9721668	0.0004451	0.0014454	0.0086588	0.0078038	0.00948
	3	0.9700066	0.0004738	0.0014522	0.008678	0.0080613	0.0113281
	4	0.9692354	0.0004763	0.0015202	0.0087876	0.0080668	0.0119136
	5	0.9686258	0.000476	0.0016047	0.0089305	0.0080661	0.012297
	6	0.9681082	0.0004757	0.0016796	0.009065	0.0080645	0.0126069
	7	0.9676662	0.0004755	0.0017445	0.0091837	0.008063	0.0128671
	8	0.9672878	0.0004752	0.0018003	0.0092865	0.0080617	0.0130883
	9	0.9669633	0.000475	0.0018482	0.0093752	0.0080606	0.0132774
	10	0.966685	0.0004749	0.0018894	0.0094516	0.0080597	0.0134395
dinf	0	0	0	0	0	0	0
	1	0.008453	0.991547	0	0	0	0
	2	0.1363823	0.8167328	0.0003178	0.0012175	0.038351	0.0069984
	3	0.1356644	0.8111655	0.0004026	0.007448	0.0381801	0.0071393
	4	0.1359321	0.8069275	0.001047	0.0109527	0.037981	0.0071597
	5	0.1363976	0.8039336	0.0015558	0.0125418	0.0378538	0.0077173
	6	0.1365717	0.8015525	0.0019485	0.0135265	0.037755	0.0086458
	7	0.1366603	0.7995042	0.0022746	0.0142286	0.0376707	0.0096616
	8	0.1367126	0.7977358	0.0025491	0.0147722	0.0375985	0.0106319
	9	0.1367463	0.7962139	0.0027821	0.0152146	0.0375367	0.0115066
	10	0.1367706	0.7949066	0.0029808	0.015584	0.0374836	0.0122744
GDP	0	0	0	0	0	0	0
	1	0.000248	0.1244075	0.8753445	0	0	0
	2	0.0416866	0.1249983	0.7153949	0.0360281	0.0393075	0.0425846
	3	0.0406547	0.1189413	0.6871837	0.0374827	0.0392673	0.0764704
	4	0.0422487	0.1155178	0.6700522	0.0375512	0.0382226	0.0964075
	5	0.0431391	0.1133057	0.6591026	0.0388187	0.037603	0.1080309
	6	0.0442008	0.1116247	0.6509712	0.0406694	0.0371283	0.1154055
	7	0.0452783	0.110263	0.6444619	0.0425878	0.0367427	0.1206662
	8	0.0462561	0.109134	0.6390952	0.0443655	0.0364219	0.1247272
	9	0.0471114	0.1081875	0.6346081	0.0459356	0.0361523	0.128005
	10	0.0478478	0.1073893	0.6308287	0.0472931	0.0359246	0.1307165
SIZE	0	0	0	0	0	0	0
	1	0.0760789	0.00041	0.1182787	0.8052324	0	0
	2	0.1515874	0.0002724	0.128117	0.6789858	0.0006015	0.040436
	3	0.1661182	0.0002163	0.1303426	0.6034511	0.0014047	0.0984672
	4	0.1681508	0.0001791	0.1304708	0.5507932	0.0019672	0.1484389
	5	0.1674883	0.0001555	0.1300421	0.5133815	0.0023643	0.1865683
	6	0.1662933	0.0001397	0.129537	0.4864301	0.0026478	0.2149522
	7	0.1651525	0.0001284	0.1290906	0.4665989	0.0028549	0.2361747
	8	0.164196	0.0001201	0.1287256	0.4516775	0.0030102	0.2522706
	9	0.163423	0.0001138	0.1284339	0.440217	0.0031292	0.2646831
	10	0.1628033	0.0001089	0.1282011	0.431255	0.0032222	0.2744095

Response variable And Fore-cast	horizon	dnpls Impulse	dinf	GDP	SIZE	RIR	CAP
RIR	0	0	0	0	0	0	0
	1	0.0307534	0.0713638	0.0164208	0.0670999	0.814362	0
	2	0.0681725	0.0550394	0.0283881	0.2439895	0.6043695	0.0000409
	3	0.085736	0.0491576	0.0426521	0.2741243	0.5400361	0.0082937
	4	0.0960801	0.0457727	0.0492851	0.2786145	0.5030038	0.0272439
	5	0.1001415	0.0433145	0.0536055	0.2792477	0.4762369	0.047454
	6	0.1028058	0.0413861	0.0568521	0.2784376	0.4552559	0.0652625
	7	0.104727	0.0398523	0.0593679	0.2772675	0.4385748	0.0802105
	8	0.1061778	0.0386188	0.0613634	0.2761251	0.4251605	0.0925545
	9	0.1073196	0.0376166	0.0629733	0.2751153	0.4142632	0.1027121
	10	0.1082405	0.0367954	0.0642879	0.2742543	0.4053338	0.1110881
CAP	0	0	0	0	0	0	0
	1	0.0015285	0.0001158	0.0038124	0.3507082	0.0013957	0.6424394
	2	0.0181749	0.0003176	0.0066896	0.3668159	0.0019801	0.6060219
	3	0.0251124	0.0003382	0.0079447	0.3721284	0.001952	0.5925242
	4	0.0275177	0.0003418	0.0086404	0.3746083	0.0019302	0.5869616
	5	0.0285623	0.0003415	0.0091164	0.3755703	0.0019266	0.5844829
	6	0.0291452	0.0003408	0.0094769	0.3758021	0.0019298	0.5833053
	7	0.0295291	0.00034	0.009765	0.3757333	0.0019352	0.5826975
	8	0.0298122	0.0003393	0.0100029	0.3755589	0.0019409	0.5823459
	9	0.0300363	0.0003388	0.0102029	0.3753603	0.0019462	0.5821156
	10	0.0302207	0.0003383	0.0103726	0.3751694	0.001951	0.581948

Source: Primary data analysis output

Looking into the results of variance decomposition (see **Table 11**), we notice that 98.59% of the change in credit risk of Islamic banks is explained by itself, and only 0.58%, 0.32%, 0.24%, 0.24%, 0.21% and 0.02% of the change in credit risk is explained by inflation rate, solvency, GDP growth rate, real interest rate and bank size shocks, successively.

Table 11. FEVD: Forecast-error variance decomposition for islamic banks

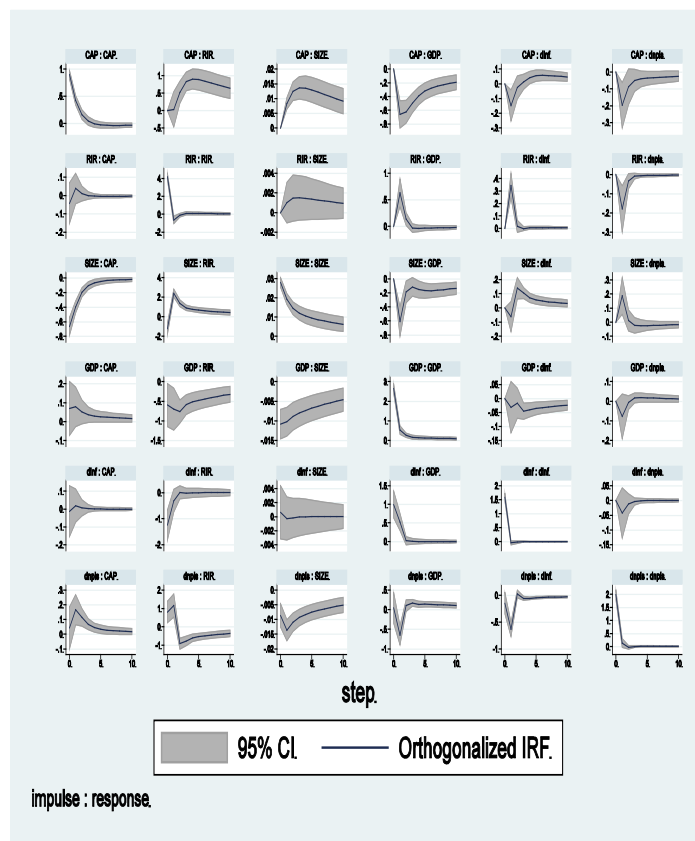
Response variable And Fore-cast	horizon	dnpls Impulse	dinf	GDP	SIZE	dRIR	CAP
dnpls	0	0	0	0	0	0	0
	1	1	0	0	0	0	0
	2	0.985906	0.005871	0.0024366	0.000289	0.00219	0.0032
	3	0.980304	0.0059016	0.0024552	0.000853	0.003073	0.0074
	4	0.978436	0.0058877	0.0025212	0.001354	0.003169	0.0086
	5	0.977387	0.0058927	0.0025295	0.002053	0.003181	0.0089
	6	0.976477	0.0058881	0.0025373	0.002946	0.003180	0.0089
	7	0.975428	0.0058816	0.0025883	0.003904	0.003179	0.0090
	8	0.974097	0.0058754	0.0026953	0.004836	0.003190	0.0093
	9	0.972492	0.0058708	0.0028537	0.005672	0.003218	0.0098
	10	0.970712	0.0058682	0.0030462	0.006366	0.003262	0.0107
dinf	0	0	0	0	0	0	0
	1	0.021002	0.9789976	0	0	0	0
	2	0.029646	0.9339151	0.0097242	0.000897	0.009135	0.0166
	3	0.030845	0.9295444	0.0010772	0.000973	0.009141	0.0187
	4	0.03078	0.9274898	0.011028	0.000971	0.009177	0.0205
	5	0.030835	0.9261448	0.0110897	0.001036	0.009250	0.0216
	6	0.03088	0.9254241	0.011115	0.001177	0.009275	0.0221
	7	0.030915	0.925014	0.0111144	0.001399	0.009282	0.0222
	8	0.030934	0.9247062	0.011112	0.001681	0.009280	0.0222
	9	0.030940	0.9243805	0.0111219	0.001993	0.009277	0.0222
	10	0.030934	0.9239794	0.0111495	0.002304	0.009277	0.0223
GDP	0	0	0	0	0	0	0
	1	0.005429	0.0269467	0.9676239	0	0	0
	2	0.05145	0.0323054	0.8664137	0.023218	0.006422	0.0201
	3	0.051431	0.0302155	0.8031638	0.082699	0.007601	0.0248
	4	0.052323	0.02825	0.7519677	0.135778	0.00710	0.0245
	5	0.049710	0.0262187	0.7015805	0.179456	0.007311	0.035
	6	0.045983	0.0242601	0.6513228	0.21022	0.008185	0.0600
	7	0.042081	0.0225363	0.6045365	0.227723	0.009653	0.0934
	8	0.038627	0.0211178	0.5638919	0.234731	0.011413	0.1302
	9	0.035900	0.0200179	0.5304751	0.23475	0.013191	0.1656
	10	0.033936	0.0192031	0.504146	0.230856	0.014819	0.1970

Response variable And Fore-cast	horizon	dnpls Impulse	dinf	GDP	SIZE	dRIR	CAP
SIZE	0	0	0	0	0	0	0
	1	0.019602	0.0008742	0.0051565	0.974366	0	0
	2	0.022642	0.0006387	0.0348948	0.884056	0.002532	0.0552
	3	0.017105	0.0011848	0.0562691	0.776587	0.007282	0.1415
	4	0.012088	0.0019463	0.0711574	0.676303	0.012207	0.2262
	5	0.008931	0.0027022	0.0812492	0.592093	0.016507	0.2985
	6	0.007283	0.0033702	0.0879727	0.524509	0.020045	0.3568
	7	0.006664	0.0039311	0.0923867	0.471419	0.022874	0.4027
	8	0.006705	0.0043893	0.0952068	0.430339	0.025095	0.4382
	9	0.007147	0.0047548	0.096913	0.399113	0.026805	0.4652
	10	0.007816	0.0050385	0.0978356	0.376003	0.028086	0.4852
dRIR	0	0	0	0	0	0	0
	1	0.025310	9.93	0.1461971	0.017717	0.810765	0
	2	0.020966	0.0454493	0.143622	0.092509	0.673420	0.0240
	3	0.036948	0.0441983	0.1366116	0.144102	0.616186	0.0219
	4	0.036091	0.0414044	0.1309584	0.183131	0.577938	0.0304
	5	0.033784	0.0384594	0.1281031	0.213087	0.536354	0.0502
	6	0.031211	0.0357437	0.1263038	0.231093	0.495889	0.0797
	7	0.028797	0.0333717	0.1250915	0.238947	0.459800	0.1139
	8	0.026852	0.0314317	0.1243059	0.239778	0.429535	0.1480
	9	0.025454	0.0299246	0.1237414	0.236449	0.405399	0.1790
	10	0.024563	0.0288004	0.1232824	0.231181	0.386938	0.2052
CAP	0	0	0	0	0	0	0
	1	0.000462	0.007612	0.0504717	0.452334	0.01903	0.4700
	2	0.000966	0.0062053	0.0746668	0.391537	0.027531	0.499
	3	0.001160	0.0060128	0.0884301	0.346420	0.02959	0.5283
	4	0.001764	0.0062647	0.0949799	0.309240	0.031514	0.5562
	5	0.002747	0.006507	0.0984247	0.279375	0.033167	0.5797
	6	0.0039	0.0067381	0.1002835	0.25596	0.034476	0.5986
	7	0.005109	0.0069385	0.1011591	0.238159	0.03548	0.6131
	8	0.00629	0.0070992	0.1014084	0.225279	0.036234	0.6236
	9	0.007392	0.0072184	0.1012634	0.216688	0.036744	0.6306
	10	0.008351	0.0072977	0.1008902	0.211741	0.037050	0.6346

Source: Primary data analysis output

Figure 3 presents the impulse responses for the entire sample of conventional banks (49). The most important responses of the credit risk of conventional banks are against credit risk in previous years, inflation rate, GDP growth rate, real interest rate, bank size and solvency shocks.

Figure 3. Impulse-Response for the Panel Vector Autoregression using the PVAR approach for conventional banks



Source: Primary data analysis output

The vector autoregressive panel's impulse response is seen in **Figure 3**. The variables are; credit risk (NPLs), inflation rate (INF), GDP growth rate (GDP), real interest rate (RIR), bank size (SIZE) and solvency (CAP).

- *Credit risk shock*: The IRF graph shows that the effect of the credit risk shock has an immediate positive impact on the future credit risk for traditional banks, with a downward trend. This implies that future non-performing loans (t) have been influenced by the shocks of non-performing loans in the previous year (t-1), then the credit risk variable is explained by itself.
- *Inflation rate shock*: The inflation rate shock has negative effects on the credit risk of conventional banks, in the short term, then it returns back and is cancelled until the end of the period, i.e. the volume of non-performing loans can be reduced after an increase in the inflation rate shock.
- *GDP growth rate shock*: Similarly, the GDP growth rate shock leads to a reduction in the credit risk of conventional banks, but in the short term with a magnitude of 1, then it returns back and is cancelled until the end of the period. We note that the shock of a higher GDP growth rate may lead to a future decline in non-performing loans.
- *Bank size shock*: It should be recognized that the short-term impact of the bank size shock on conventional banks' credit risk is positive, then its response becomes negative, and finally it is cancelled out for the rest of the period, i.e. a shock of increasing bank

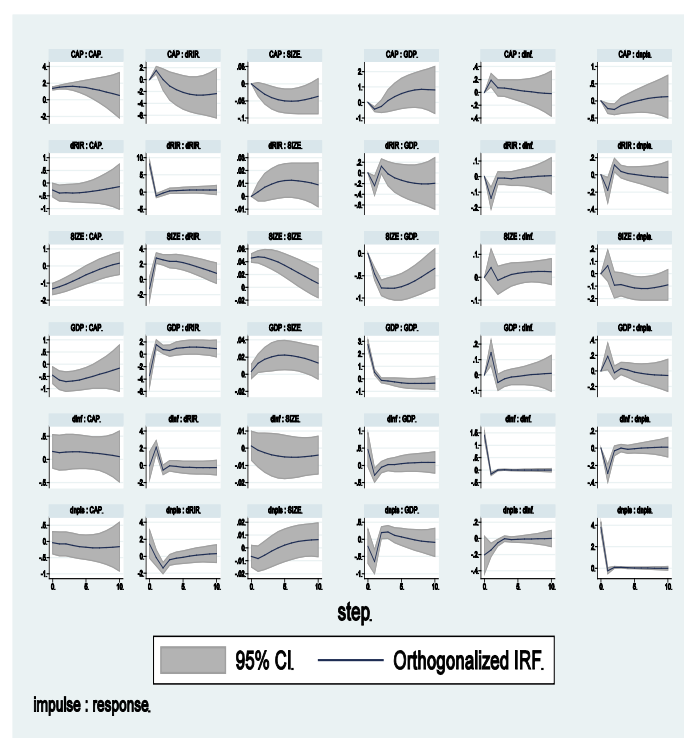
size (t) reduces the volume of future non-performing loans (t+2).

- *Solvency shock*: The solvency shock has a negative impact with a magnitude of 2 on the credit risk of conventional banks in the short-term, and then it will tend to increase until it is cancelled out for the rest of the period. This may indicate that the shock of a decrease in solvency at a given moment increases the volume of future non-performing loans.
- *Real interest rate shock*: Additionally, the real interest rate shock has a significant impact on the traditional banks' lending risk at the beginning of the period, but it begins to cancel out in the same year until the end of the period. It should also be noted that the shock of an increase in interest rates (t) reduces credit risk in the following year (t+1).

Figure 4 presents the impulse responses for the entire sample of Islamic banks (26).

The most important responses of the credit risk of Islamic banks are against credit risk in previous years, inflation rate, GDP growth rate, real interest rate, bank size and solvency shocks.

Figure 4. Impulse-Response for the Panel Vector Autoregression using the PVAR approach for islamic banks



Source: Primary data analysis output

This figure displays the panel's vector autoregressive impulse response. The variables are; credit risk (NPLs), inflation rate (INF), GDP growth rate (GDP), real interest rate (RIR), bank size (SIZE) and solvency (CAP).

Figure 4 displays the panel's vector autoregressive impulse response. The variables are; credit risk (NPLs), inflation rate (INF), GDP growth rate (GDP), real interest rate (RIR), bank size (SIZE) and solvency (CAP).

- *Credit risk shock*: The future credit risk of Islamic banks reacts instantly and positively to a credit risk shock throughout the period. The credit risk's reaction begins to reverse from the first year to the end of the period. We notice that credit risk is explained by itself with a positive sign.

- *Inflation rate shock*: Throughout the period, the inflation shock has a detrimental impact on the credit risk of Islamic institutions. The effect begins to cancel out after the first year until the end of the period. We notice that the shock of rising inflation reduces the volume of future non-performing loans.
- *GDP growth rate shock*: At the beginning of the term, credit risk responds positively to a shock in the GDP growth rate. then becomes negative after the second year. This implies that the shock of an increase in the GDP growth rate may reduce the volume of non-performing loans after the second year.
- *Bank size shock*: The response of credit risk to a bank size shock only began in the first year. It is positive with a downward trend from the second year till the end of the period. This contributes to the fact that the shock of an increase in bank size starts to reduce the volume of future non-performing loans from the second year onwards.
- *Solvency shock*: We notice that the impact of a solvency shock on the credit risk of Islamic banks is negative with a slight upward trend from the sixth year onwards, i.e. the solvency shock reduces the volume of non-performing loans in the future.
- *Real interest rate shock*: A shock of actual interest rates has a negative impact on the credit risk of Islamic banks in the first year and then a positive effect until the fifth year.

We conclude that the shock of an increase in the real interest rate increases credit risk from the third year onwards. By performing *the stationarity test* (Section 3) for Islamic and conventional banks, we found that GDP, SIZE and CAP series are stationary in level, it means that their mean and variance remain constant over time. While the NPLs, INF and RIR series are non-stationary or order (1) integrated, it suggests that these series may exhibit trends or have systematic patterns that evolve over time.

The findings of the *correlation matrix* for Islamic and conventional bank variables indicate a strong link between credit risk and Real interest rate, Bank Size and Inflation rate. This suggests that the level of credit risk may vary depending on whether real interest rates rise or fall. The relationship between bank size and credit risk may suggest that bigger banks are more or less vulnerable to credit risk. This is a result of the borrowers that larger banks serve or the diversification of their portfolios. The relationship between credit risk and inflation rate implies that both high inflation and credit risk may be correlated. Inflation can have an impact on borrowers' capacity to repay loans.

In this study, we found that a positive GDP growth rate shock leads to a negative credit risk response by Islamic and conventional banks. Positive GDP growth indicates a generally positive state of the economy. Both Islamic and conventional banks may experience a decrease in credit risk as a result of better economic conditions having a beneficial effect on borrowers' credit quality. This observation is in accord with Louzis et al (2010), Castro (2013), Chaibi and Ftiti (2015), and Darwez et al. (2023). A decrease in bank size shock increases the volume of future non-performing loans in Islamic and conventional banks. Larger banks frequently have portfolios that are more diversified, which helps reduce risk. Reduced diversification brought on by a smaller bank may increase the bank's vulnerability to particular or sector-specific risks, which would raise the number of non-performing loans (NPLs). These results are consistent with those of Salsa and Saurina (2002) and Louzis, D et al. (2012). Solvency decreases shock at a moment (t-2) increases the volume of non-performing loans in the future (t) of Islamic and conventional banks. So, the impact of a solvency shock on the credit risk is negative. Sufficient capital reduces credit risk by strengthening the bank's resilience to unfavorable economic conditions and acting as a buffer against unforeseen losses. This is consistent with the finding of Makri et al. (2014) and Chaibi and Ftiti (2015). Real interest rates increase shock increases the

credit risk of Islamic banks from the third year onwards. Increased real interest rates have the potential to cause a decline in economic activity, which could impact both individual and corporate creditworthiness. Islamic banks may have trouble controlling the credit risk connected to their financing operations if the economy worsens as a result of rising interest rates. This result is comparable to that of [Abid et al \(2014\)](#) and [Roland et al \(2013\)](#). However, a real interest rate shock negatively affects the credit risk of conventional banks. Conventional banks may see an increase in interest income as a result of higher real interest rates. By improving the credit risk profile and acting as protection against credit losses, this could raise the banking industry's overall profitability.

Stress tests are an essential tool for improving bank transparency because they offer a thorough evaluation of a bank's ability to withstand unfavorable economic conditions and possible financial shocks. Stress tests are a useful tool for identifying and evaluating the different risks that a bank might encounter in the event of recession. Stress scenarios are applied to the bank's portfolio to provide stakeholders and regulators with information about possible weaknesses.

5. CONCLUSIONS

Stress testing is an important component of the Basel II Accord in the area of risk management because it can help financial institutions better understand the effect of stress scenarios and measure their exposure to risk under extreme conditions. This would allow them to manage these risks through corrective action.

In this paper, we used the [Abrigo and Love's \(2015\)](#) Vector Autoregressive Panel methodology as a direct measure of bank fragility to study the contribution of stress tests to reduce banking opacity and improve financial resistance to adverse shocks. This approach is able to detect the magnitude of the effect of shocks over a given period by using the impulse response function (IRF) analysis and variance decomposition (FEVD). It tests the resistance of credit risk to adverse shocks. We conducted stress tests of credit risk against macroeconomic and specific shocks over a sample of 75 conventional and Islamic listed banks in 7 MENA countries. According to our knowledge, this is the first that the PVAR approach has been used to solve this issue.

The stress test consists in selecting the scenarios that define exogenous shocks, then analyzing and discussing its results to give a partial picture of risk-taking by financial institutions. Finally, the publication of these results may raise awareness of these institutions about the different risks because the market may interpret this information negatively.

The results of the impulse response functions provide statistically significant evidence on the strong effect of the different macroeconomic and specific shocks on the credit risks of conventional and Islamic banks in the MENA region. As a result, our findings indicate that there are few significant differences between Islamic and conventional banks in terms of how they respond to extreme shocks in terms of credit risk. However, these results provide information on the resistance of the tested banks to the different studied shocks.

We conclude that the results of stress tests are associated with significant changes (positive or negative) in credit risk. In addition, our results confirm that most macroeconomic and specific determinants are in fact early warnings for shock prediction. This shows evidence that stress tests produce information about credit risk exposure and about the real conditions of financial institutions. Which reduce the opacity bank.

By simulating loss distributions in financial institution portfolios, it appears that these tests evaluate the consequences of growing fragility on the macroeconomic environment and on the

financial system's long-term stability. Therefore, more transparency on bank losses and risks would have also enabled bank regulators to focus more attention on financial institutions and react early to take "corrective measures" through the recapitalization of failing or insolvent banks.

Similarly, our results show that it is possible to integrate modern banking activities such as stress testing into studying Islamic banks. Therefore, our study may be of interest to international investors and portfolio managers since the publication of information on the resistance of the tested banks against adverse shocks may change their expectations. Otherwise, Stress tests are incredibly important when it comes to evaluating how well a bank can handle situations. By conducting these tests policymakers can pinpoint any weaknesses, in the banking system. Take steps to improve overall financial stability. The significance of stress tests doesn't just stop there. They also help refine frameworks and enhance transparency in the banking industry. Policymakers should view stress tests as a tool, for assessing and managing risks ultimately leading to an more transparent financial system.

Further research can explore the impact of stress tests on improving the stock performance of conventional banks in regions outside of the MENA countries during the Covid 19 crisis.

ACKNOWLEDGMENT

'This work was supported through the Annual Funding track by the Deanship of Scientific Research, Vice Presidency for Graduate Studies and Scientific Research, King Faisal University, Saudi Arabia [Project No GRANT 5565]

REFERENCE

- Abad, P., Robles, M.-D. and 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. <https://doi.org/10.1016/j.intfin.2023.101876>
- Abdymomunov, A. and 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. and Zouari-Ghorbel, S. (2014). Macroeconomic and Bank-specific Determinants of Household's Non-performing Loans in Tunisia: A Dynamic Panel Data. *Procedia Economics and Finance*, 13, 58–68. [https://doi.org/10.1016/S2212-5671\(14\)00430-4](https://doi.org/10.1016/S2212-5671(14)00430-4)
- Abrigo, M.R.M. and Love, I. (2016). Estimation of Panel Vector Autoregression in Stata. *The Stata Journal: Promoting Communications on Statistics and Stata*, 16 (3), 778–804. <https://doi.org/10.1177/1536867X1601600314>
- Acharya, V. V., Engle, R. F., & Melzer, M. (2012). Financial market reactions to stress tests. *Journal of Monetary Economics*, 59(1), 102-119. <https://www.sciencedirect.com/journal/journal-of-monetary-economics>
- Agarwal, V., D. Chambers, and M. McQuinn. (2009). The impact of stress tests on bank lending and credit risk. *Journal of Finance*, 64(6), 2537-2572. <https://onlinelibrary.wiley.com/journal/15406261>
- Akinlo, O. and Emmanuel, M. (2014). Determinants of non-performing loans in Nigeria. *Accounting & Taxation*, 6(2), 21–28. Stress testing in Islamic banking: Challenges and opportunities <https://doi.org/10.14738/abr.51.2368>
- Al-Haddad, A., Haron, N. A., & Majid, M. Z. (2015). Stress testing in Islamic banking: Challenges and opportunities. *Journal of Islamic Banking and Finance*, 3(2), 163-179. <http://jibfnet.com/vol-3-no-2-december-2015-jibf>
- Al-Hussainy, F., R. Hassan, and C. R. Nelson (2016). Stress testing in Islamic banking: Issues and challenges. *Journal of Banking and Finance*, 69, 389-400. <https://www.sciencedirect.com/journal/journal-of-banking-and-finance/vol/69/suppl/C>
- Al-Khater, M. A., Al-Khater, H. H., & Jantan, M. N. (2019). Stress testing in Islamic banks: A review of the literature. *International Journal of Financial Studies*, 7(2), 24. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3840056
- Ameer, W., Xu, H., Sohag, K., Halwan, M.M. and Amin, A. (2022). Research methods in economics and its implications for capital formation. *Economic Research-Ekonomska Istraživanja*, 35(1), 5536–5555, <https://doi.org/10.1080/1331677X.2022.2030244>
- Amin, A., Bte Mohamed Yusoff, N.Y., Yousaf, H., Peng, S., Işık, C., Akbar, M. and Abbas, S. (2023). The influence of renewable and non-renewable energy on carbon emissions in Pakistan: evidence from stochastic impacts by regression on population, affluence, and technology model. *Frontiers in Environmental Science*, 11, 1182055, <https://doi.org/10.3389/fenvs.2023.1182055>
- BCBS; Basel Committee on Banking Supervision (2009). Principles for sound stress testing practices and supervision, Bank for International Settlements. *Working paper*. <https://www.bis.org/publ/bcbs147.pdf>
- Beck, R., Jakubik, P. and Piloju, A. (2013). Non-Performing Loans: What Matters in Addition to the Economic Cycle? *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2214971>
- Blau, B.M., Brough, T.J. and 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>
- Bofondi, M. and Ropele, T. (2011). Macroeconomic Determinants of Bad Loans: Evidence from Italian Banks. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.1849872>

- Brown, S., R. F. Green, and M. Manely. (2011). Stress testing as a regulatory tool: How it has evolved and how it might be improved. *Journal of Financial Intermediation*, 20(2), 311-327. <https://www.sciencedirect.com/journal/journal-of-financial-intermediation/vol/20/issue/3>
- Brunnermeier, M. K., Cherny, A., & Sunderesen, S. (2016). Stress testing. *Handbook of Macroeconomics*, 2, 209-272.
- 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. and Fiti, 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>
- Chakrabarti, M. (2015). Risk analysis and management in Indian banking sector: An overview. *International Journal of Informative & Futuristic Research*, 2 (7), 2133–2143. https://www.academia.edu/15832062/Risk_Analysis_And_Management_In_Indian_Banking_Sector_An_Overview
- Commission, U.S.F.C.I. (2010). The Financial Crisis Inquiry Report: Final Report of the National Commission on the Causes of the Financial and Economic Crisis in the United States, Government Printing Office. <https://www.govinfo.gov/app/details/GPO-FCIC>
- De Mendonça, H.F., Galvão, D.J.C. and 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>
- Darwez, F., Alharbi, F., Ifa, A., Bayomei, S., Mostfa, E., Lutfi, A. and Alrawad, M. (2023). Assessing the Impact of Oil Price Volatility on Food Prices in Saudi Arabia: Insights From Nonlinear Autoregressive Distributed Lags (NARDL) Analysis. *ECONOMICS-Innovative and Economics Research Journal*, 11(2), 5–23. <https://doi.org/10.2478/eoik-2023-0056>
- Dluhopolskyi, O., Kozlovskyi, S., Popovskyi, Y., Lutkovska, S., Butenko, V., Popovskyi, T., ... & Kozlovskyi, A. (2023). Formation of the Model of Sustainable Economic Development of Renewable Energy. *ECONOMICS-Innovative and Economics Research Journal*, 11(2), 51-78. <https://doi.org/10.2478/eoik-2023-0050>
- Ellahie, A. (2012). Bank stress tests and information asymmetry. Annual Meeting and Conference on Teaching and Learning Accounting, American Accounting Association, Washington Dc. <https://aaahq.org/Meetings/2022/CTLA>
- Erkişi, K. and Boğa, S. (2023). Does Financial Inclusion Improve Income Equality? The Case of Türkiye. *ECONOMICS- Innovative and Economics Research Journal*, 11(2), 79–95. <https://doi.org/10.2478/eoik-2023-0049>
- FCIR (2011). The Financial Crisis Inquiry Report, Final Report of The National Commission On The Causes Of The Financial And Economic Crisis In The United States. Official Government Edition. Réalisé par The Financial Crisis Inquiry Commission. <https://www.govinfo.gov/app/details/GPO-FCIC>
- Flannery, M., Hirtle, B. and 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>
- Flannery, M.J., Kwan, S.H. and 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>
- Ghosh, A. (2015). Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states. *Journal of Financial Stability*, 20, 93–104. <https://doi.org/10.1016/j.jfs.2015.08.004>
- Gick, W.H. and Pausch, T. (2012). Optimal Disclosure of Supervisory Information in the Banking Sector. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2006852>

- Goldstein, I. (2014). Should Banks' Stress Test Results be Disclosed? An Analysis of the Costs and Benefits. *Foundations and Trends® in Finance*, 8 (1), 1–54. <https://doi.org/10.1561/05000000038>
- Halwan, M.M., Bin, Z.Y., Ameer, W., Mumtaz, N., Mumtaz, A. and Amin, A. (2022). Research Methods in a Multinational Business Environment and Implications for Capital Formation: Application of Cross-Sectional Autoregressive Distributed Lag Methods. *Frontiers in Psychology*, 13. <https://doi.org/10.3389/fpsyg.2022.867891>
- Hilbers, M.P.L.C., Jones, M.M.T. and Slack, M.G.L. (2004). Stress Testing Financial Systems: What to Do When the Governor Calls. International Monetary Fund.
- Iqbal, Z., and P. Molyneux. (2015). Stress testing and Sharia-compliant banking. In *Stress Testing in the Financial Industry*, edited by F. Allen, R. Cont, and D. Gorton, 135-160. Springer, New York, NY.
- Jawadi, F. and Louhichi, W. (2017). Overview on the recent developments of banking and risk management. *Research in International Business and Finance*, 39, 896–898. <https://doi.org/10.1016/j.ribaf.2016.11.001>
- Jedidia, K.B. (2018). Do Islamic banking standards convey more financial transparency than conventional banking ones? *Turkish Journal of Islamic Economics*, 5 (1), 109–132. <https://doi.org/10.26414/tujise.2018.5.1.109-132>
- Kasman, S., Vardar, G. and Tunç, G. (2011). The impact of interest rate and exchange rate volatility on banks' stock returns and volatility: Evidence from Turkey. *Economic Modelling*, 28(3), 1328–1334. <https://doi.org/10.1016/j.econmod.2011.01.015>
- Khan, B. . (2023). CO2 Emissions and Economic Growth in Some Selected Countries of Ecowas: Panel Data Approach. *ECONOMICS-Innovative and Economics Research Journal*, 11(2), 245–256. <https://doi.org/10.2478/eoik-2023-0055>
- Khaled m Alqudah, M. N. ., & Yusof, Y. . (2024). Improving Environmental Performance Through Innovative Academic Citizenship Behaviour: Green Training And Development, Green Recruitment And Selection As Antecedents In Jordanian Government University. *ECONOMICS-Innovative and Economics Research Journal*, 12(1). <https://sciendo.com/article/10.2478/eoik-2024-0002>
- Khammassi, I. and Naoui, K. (2019). Credit risk and bank opacity: a comparative study of conventional and Islamic banks. *American J. of Finance and Accounting*, 6 (1), 56. <https://doi.org/10.1504/AJFA.2019.104192>
- Khammassi, I., Boufateh, T. and Naoui, K. (2020). Do stress tests reduce liquidity risk opacity. *American J. of Finance and Accounting*, 6 (2), 135. <https://doi.org/10.1504/AJFA.2020.110322>
- Kok, C., Müller, C., Ongena, S. and Pancaro, C. (2023). The disciplining effect of supervisory scrutiny in the EU-wide stress test. *Journal of Financial Intermediation*, 53. <https://doi.org/10.1016/j.jfi.2022.101015>
- Kosmidou, K., Kousenidis, D., Ladas, A. and Negkakis, C. (2017). Determinants of risk in the banking sector during the European Financial Crisis. *Journal of Financial Stability*, 33, 285–296. <https://doi.org/10.1016/j.jfs.2017.06.006>
- Kucukkocaoglu, G. and Altintas, M.A. (2016). Using non-performing loan ratios as default rates in the estimation of credit losses and macroeconomic credit risk stress testing: A case from Turkey. *Risk Governance and Control: Financial Markets & Institutions*, 6 (1). <https://doi.org/10.22495/rgcv6i1art6>
- Louzis, D.P., Vouldis, A.T. and 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. and Bellas, A. (2014). Determinants of non-performing loans: The case of Eurozone. *Panoeconomicus*, 61(2), 193–206. <https://doi.org/10.2298/PAN1402193M>
- Matthew T. et al (2004). Stress testing financial systems: What to do when the governor calls. Chicago: IMF.
- Mayer, C., Pence, K. and Sherlund, S.M. (2009). The Rise in Mortgage Defaults. *Journal of Economic Perspectives*, 23(1), 27–50. <https://doi.org/10.1257/jep.23.1.27>
- 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>
- Myers, S.C. and 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](https://doi.org/10.1016/0304-405X(84)90023-0)
- Petrella, G. and 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>
- Rahman, A.A., Ibrahim, M.H. and Meera, A.K.M. (2009). Lending structure and bank insolvency risk: a comparative study between Islamic and conventional banks. World Business Institute.
- Roland. B et al (2013) Non-performing loans: what matters in addition to the economic cycle?, ECB Working Paper No. 1515.
- Salas, V. and 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>
- Schuermann, T. (2010). Stress tests and bank disclosure: The European experience. *Journal of Financial Intermediation*, 19(4), 587–602. <https://www.sciencedirect.com/journal/journal-of-financial-intermediation>
- Shank, C.A. and 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>
- Singh. S.K et al (2021). The Effect of Non-Performing Loan on Profitability: Empirical Evidence from Nepalese Commercial Banks. *Journal of Asian Finance, Economics and Business*, 8 (4), 709–716. <https://doi.org/10.13106/jafeb.2021.vol8.no4.0709>
- Stephen Kingu, P., Macha, D.S. and Gwahula, D.R. (2018). Impact of Non-Performing Loans on Bank's Profitability: Empirical Evidence from Commercial Banks in Tanzania. *International Journal of Scientific Research and Management*, 6 (1). <https://doi.org/10.18535/ijssrm/v6i1.em11>
- Supervision, B.C. on B. (2009). Principles for sound stress testing practices and supervision. Bank for International Settlements Basel.
- Sudhana Rao, K. ., Kolluru, M. ., & Hyams-Ssekasi, D. . (2022). Emerging Change: Exploring the New Economy Paradigm. *ECONOMICS-Innovative and Economics Research Journal*, 10(1). <https://doi.org/10.2478/eoik-2022-0011>
- Topić-Pavković, B., Kovačević, S. ., & Kurušić, D. (2023). The Impact of Innovative Financial and Banking Development on the Economic Growth of Bosnia and Herzegovina. *ECONOMICS-Innovative and Economics Research Journal*, 11(1), 251–267. <https://doi.org/10.2478/eoik-2022-0022>
- Ullah, A., Zhao, X., Amin, A., Syed, A.A. and Riaz, A. (2022). Impact of COVID-19 and economic policy uncertainty on China's stock market returns: evidence from quantile-on-quantile and causality-in-quantiles approaches. *Environmental Science and Pollution Research*, 30 (5), 12596–12607. <https://doi.org/10.1007/s11356-022-22680-y>

- Ullah, A., Zhao, X., Sayed, A.A., Amin, A. and Riaz, A. (2023). Impact of COVID-19 on China's business and economic conditions: the importance of quantile asymmetries. *Environmental Science and Pollution Research*, 30 (22), 61766–61777. <https://doi.org/10.1007/s11356-023-26252-6>
- Ujkani, X., & Gara, A. (2023). Determinants of the Inflation Rate: Evidence from Panel Data. *ECONOMICS-Innovative and Economics Research Journal*, 11(2), 169–182. <https://doi.org/10.2478/eoik-2023-0054>
- Vogiazas, S.D. and Nikolaidou, E. (2011). Investigating the Determinants of Nonperforming Loans in the Romanian Banking System: An Empirical Study with Reference to the Greek Crisis. *Economics Research International*, 1–13. <https://doi.org/10.1155/2011/214689>
- Yu, Z., Kamran, H.W., Amin, A., Ahmed, B. and Peng, S. (2023). Sustainable synergy via clean energy technologies and efficiency dynamics. *Renewable and Sustainable Energy Reviews*, 187. <https://doi.org/10.1016/j.rser.2023.113744>