Comparative Analysis of Risks and Their Impacts on the Banking Stability of Islamic and Conventional Banks in the MENA Region

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Abstract

This study aims to analyze and compare the impact of risks on banking stability associated with Islamic banks in comparison to their conventional counterparts in the MENA region. In this process, we first examine the correlation between liquidity risk and credit risk. Secondly, we assess whether these two types of risks are related to banking stability within both categories of banks. Using the PVAR (Panel Vector Auto Regression) econometric model on a sample of 110 conventional and Islamic banks in the MENA region, our results indicate that liquidity risk and credit risk exhibit a negative relationship in both types of banks. Furthermore, our findings suggest that there is no correlation between these risks and banking stability in both types of banks. Our conclusions have significant implications for banking institutions regarding the strategies and approaches required to manage these risks and ensure the stability of their banking operations.

Keywords: liquidity risk, credit risk, banking stability, Islamic bank, conventional bank, PVAR

1. Introduction

The stability of the banking sector is of paramount importance for sustainable economic growth and the preservation of investor confidence. Banks play a central role in maintaining this stability by acting as intermediaries between depositors and borrowers.

The banking system plays a pivotal role in the global economy by promoting a more efficient allocation of financial resources. Within the international banking sector, two primary types of banks exist: Islamic banks, which adhere to Sharia principles, and conventional banks that operate according to traditional financial system practices. Conventional banks face various operational challenges, including exposure to risks such as liquidity risk and credit risk, which have implications for banking stability and the prevention of banking crises.

Islamic banks operate in accordance with ethical principles, including the prohibition of interest (Riba), the prohibition of activities based on uncertainty (Gharar), and the practice of profit and loss sharing. However, despite their adherence to Sharia'a, they are not exempt from the common risks associated with the conventional banking system.

Several empirical studies have examined the impacts of liquidity risk and credit risk on the stability of the banking sector. It is worth noting that these empirical works have not reached a consensus on their conclusions and can be categorized into three streams. The first stream of research supports the negative effect of these two risks on banking stability (Ghenimi and al., 2017; Louati and al., 2015). The second stream of findings highlights a positive effect of these two risks on banking stability (Acharya and Mora, 2013; Adusei, 2015; Imbierowicz and Rauch, 2014; Khemais, 2019). Finally, the third stream of the literature indicates an insignificant impact of liquidity and credit risks on the stability of the banking sector (Amara and Mabrouki, 2019). These empirical analyses are primarily focused on the traditional banking sector. However, there have been limited studies examining the relationship between liquidity or credit risk and the performance or profitability of Islamic banks.

To address this gap in the literature, this paper aims to conduct a comparative analysis of the impact of liquidity risk and credit risk on banking stability in both Islamic and conventional banks. Our study adds value to the existing literature on liquidity and credit risks and their effects on the banking stability of both types of banks by examining the reciprocal relationship between liquidity risk and credit risk and how these two risks influence banking stability.

First, we will investigate whether there is a reciprocal relationship between liquidity risk and credit risk and whether this relationship is positive or negative. In light of this result, in the second phase, we will test whether liquidity risk and credit risk have an impact on banking stability in both Islamic and conventional banks. The comparative analysis between the two types of banks will help us better understand how their operational differences affect their resilience to financial risks and their ability to maintain stability in a constantly evolving economic environment. This contribution can assist bank supervisors in monitoring and assessing the stability of both the Islamic and conventional banking systems and their determinants.

In this paper, we will use the Panel Vector AutoRegression (PVAR) econometric model. The study will focus on a panel of 110 conventional and Islamic banks in the MENA region over the period 2005-2021.

The remainder of this paper is organized as follows. Section 2 provides a literature review, Section 3 focuses on data and methodology, Section 4 addresses empirical results and their interpretation, and finally, Section 5 presents the conclusion.

2. Literature Review and Hypotheses Development

For a long time, the literature review has focused on the liquidity and credit risk of banks. Theoretically, liquidity risk and credit risk should be positively correlated. This hypothesis is supported by the theoretical literature on financial intermediation, as modeled by Bryant (1980) and Diamond and Dybvig (1983). These studies have shown that banks' risky assets, combined with uncertainty about liquidity needs, can trigger panics.

Many studies, especially after the Subprime crisis, emphasize the existence of a positive relationship between these two risks (Allen and Carletti, 2008; Cornette and al., 2011; Nikomara and al., 2013; Imbierowicz and Rauch, 2014; Louati and al., 2015).

Nikomara et al. (2013) studied the relationship between credit and liquidity risks for Iranian banks. The study included all private and government banks over the period 2005-2012. They concluded that there is a positive and significant relationship between credit and liquidity risks.

Imbierowicz and Rauch (2014) tested the relationship between liquidity risk and credit risk in U.S. banks. Their study encompassed a sample of all commercial banks in the United States over the period 1998-2010. They demonstrated a positive relationship between liquidity risk and credit risk but found no reciprocal relationship between the two risks.

Louati and al. (2015) examined and compared the behavior of Islamic and conventional banks regarding the capital adequacy ratio. The authors used data from 12 countries in the Middle East and Southeast Asia over the period 2005-2012. They showed that there is a significant and negative relationship between liquidity risk and credit risk in conventional banks.

The studies presented below have primarily focused on the conventional banking system. However, Islamic banks operate alongside conventional banks worldwide, offering similar services to meet the needs of all stakeholders but using different contractual structures (Hennie and Iqbal, 2008). Therefore, based on the same knowledge base as conventional banks, we posit that there is a relationship between liquidity risk and credit risk within Islamic banks. Thus, we formulate our first hypothesis as follows:

H1: There is a relationship between liquidity risk and credit risk in both Islamic and conventional banks.

The effects of credit and liquidity risks on the stability of banks have been the subject of several empirical studies (Acharya and Mora, 2013; Adusei, 2015; Amara and Mabrouki, 2019; DeYoung and Jang, 2016; Imbierowicz and Rauch, 2014; Khemais, 2019; etc.). These studies primarily focus on the relationship between liquidity risk or credit risk and banking stability. However, their results are not unanimous.

The negative impact of credit and liquidity risks on banking stability has been analyzed in several studies. In this regard, the study by Ghenimi et al. (2017), using data from 49 conventional banks in the MENA region over the period 2006-2013, did not reveal a correlation between liquidity risk and credit risk. However, it highlighted that these two types of risks influence both individual and joint stability of banks.

Adusei (2015) analyzed quarterly data from 2009 to 2013 to identify the main factors disrupting the rural banking sector in Ghana. The results indicated that credit risk undermines the stability of banks when assessed using certain indicators.

According to Acharya and Mora (2013), the role of banks as liquidity providers was crucial during the 2008 financial crisis. Their findings highlighted that banks that failed during this crisis faced liquidity-related difficulties. These results suggest that the coexistence of liquidity and credit risks could increase the risk of bank failures.

In a comparative study conducted for the period 2006-2009, Rajhi and Hassairi (2013) advanced the idea that credit risk decreases the stability of banks in the MENA region. Their analysis revealed that credit risk, assessed using the ratio of loan loss provisions to net interest income, leads to a decrease in the Z-score of small banks operating in countries in the MENA region.

Using panel data analysis covering the period 2005-2015, Khemais (2019) studied the impact of credit, liquidity, and operational risks on the stability of traditional banks in Tunisia. The empirical results indicate that credit risk represents a threat to the stability of Tunisian banks. Furthermore, the interaction between credit and liquidity risks also exacerbates their stability. However, other researchers put forward the idea that credit and liquidity risks have a positive impact on bank stability because profitability and risks are closely linked. In this perspective, credit and liquidity risk does not seem to undermine bank stability.

Another group of studies adheres to the neutrality hypothesis, suggesting that credit and liquidity risks do not have a significant impact on bank stability. In this regard, Amara and Mabrouki (2019) examined the relationship between liquidity and credit risks and their influence on bank stability in Tunisia over the period 2006-2015. Their results indicate that credit risk and liquidity risk do not have an economically significant reciprocal relationship, and each type of risk has only a minor impact on banking stability. Additionally, the authors concluded that the interaction between the two risks has an insignificant effect on bank stability.

Thus, drawing from the literature and the arguments mentioned above, we formulate the following hypotheses for our study:

H2: There is a relationship between liquidity risk and financial stability in both Islamic and conventional banks.

H3: There is a relationship between credit risk and financial stability in both Islamic and conventional banks.

These empirical studies have extensively investigated the implications of liquidity risk and credit risk on the stability of the banking sector. However, these studies have yielded diverse conclusions, leading to categorization into three main streams. The first stream suggests a detrimental effect of both liquidity and credit risks on banking stability. Conversely, the second stream of findings, indicates a positive relationship between these risks and banking stability. Finally, the third stream of literature suggests an insignificant impact of liquidity and credit risks on banking stability.

Primarily focusing on the traditional banking sector, these empirical analyses underscore the need for further investigation into the relationship between liquidity and credit risks and the performance or profitability of Islamic banks. Consequently, this paper seeks to bridge this gap by undertaking a comparative analysis of the influence of liquidity risk and credit risk on banking stability in both Islamic and conventional banks. By exploring the interplay between liquidity risk and credit risk and their collective impact on banking stability, our study aims to enrich the existing literature on these risks and their implications for the stability of both types of banks.

3. Data and Methodology

In this section, we provide a brief explanation of the data and methodology used in our modeling.

3.1 Data

This paper focuses on Islamic banks and their conventional counterparts operating in countries within the MENA region. The choice of this region is driven by several considerations. Firstly, the credit growth rates in the MENA region have exhibited more pronounced volatility, raising concerns about the stability of the financial system. Additionally, countries in the MENA region have attracted attention from bankers and investors worldwide, increasing the region's vulnerability to political, economic, and financial instability. Thus, the presence of Islamic banks can influence the stability of conventional banks. However, while banks in the MENA region are recovering from the recent financial crisis, ongoing political turmoil and sudden regime changes have the potential to hinder economic growth and destabilize banking institutions.

This study uses annual data obtained from the Datastream database. Macroeconomic and country-specific variables are extracted from indicators published on the World Bank's website. The panel data includes 110 banks, comprising 82 conventional banks and 28 Islamic banks from ten countries: Bahrain, Lebanon, Qatar, Saudi Arabia, Tunisia, the United Arab Emirates, Kuwait, Syria, Egypt, and Yemen. The sample period spans from 2005 to 2021.

Our study employs both internal and external bank variables as explanatory variables. The dependent variables include credit risk, liquidity risk, and bank stability. Table 1 presents the various variables used in the modeling, their definitions, and their measurements.

Table 1. Model Variables

Names	Notation	Unit	Measure	Sources
			Dependent variables	
Liquidity Risk	RL	%	Liquid Assets / Total Assets.	Ghenimi et al. (2017) Amara et Mabrouki (2019).
Credit Risk	NPL	%	Performing Loan / Gross Loan	Cai and Zhang (2017) Mpofu et Nikolaidou (2018) Natsir et al. (2019).
Bank stability	Z-SCORE	%	(ROA+ CAR) / σ (ROA)	Laeven et Levine (2008) Hakimi, et al, (2017) Amara et Mabrouki (2019).
			Independent variables	
Size of bank	Taille		Ln (total assets)	Anginer, et al, (2014) Hakimi et al. (2017).
Return on Equity	ROE	%	Net income / total assets	Brigham et Houston (2018) Rosset al (2019)
Return on Assets	ROA	%	Net income / total liabilities	Rashid et Jabeen (2016) Amara and Mabrouki (2019).
Liquidity Gap	EL	USD	Ln (Total assets - Total liabilities)	Loutskina et Strahan (2009) Vithessonthi et Tongurai (2018)
Loan Assets	AP	%	Net loans / Total assets	Altunbaş et al. (2010) Chen et Lobo (2012) Bostandzic et Flavin (2015)
Adequate Capital	CAR	%	Equity / Total assets	Pathan (2009) Hakimi et al. (2017).
			Macroeconomic variables	
Inflation rate	INF	%	Consumer Price	Imbierowicz et Rauch (2014) Kharabsheh (2019).
Gross Domestic Product	GDP	%	GDP per capita	Ghenimi et al. (2017) Hakimi et Zaghdoudi (2017) Djebali et Zaghdoudi (2020)

3.2 Methodology

This study employs a Panel Vector Autoregressive (PVAR) model to examine, on the one hand, the reciprocal relationship between liquidity risk and credit risk, and, on the other hand, to assess the impact of these two risks on the bank stability of Islamic and conventional banks in the MENA region. This approach combines the classic VAR method, which treats all variables in the system as endogenous, with a panel data methodology that accounts for unobserved individual heterogeneity. The econometric regression is estimated by the following equation:

$$Y_{i,t} = \alpha_i + \varphi(l)Y_{i,t} + \mu_{i,t} + \vartheta_i + \varepsilon_{i,t} \quad (1)$$

Where i = 1, ..., N represents the banks, and t = 1, ..., T represents the time periods.

$Y_{i,t}$ is a column vector of observed panel series variables (liquidity risk (RL), credit risk (PNL), and bank stability (Z-score).

$\mu_{i,t}$ is a matrix of control variables for the panel series (bank-specific control variables including ROA, ROE, AP, EL, bank size, and CAR, and macroeconomic variables such as inflation rate and GDP).

$\varepsilon_{i,t}$ is the vector of errors with their usual assumptions.

$\varepsilon_{i,t}$ est le vecteur des erreurs avec ses hypothèses habituelles.

$$\begin{pmatrix} \text{RL} \\ \text{PNL} \\ \text{Z-score} \end{pmatrix} = \alpha_i + \varphi(l) \begin{pmatrix} \text{RL} \\ \text{PNL} \\ \text{Z-score} \end{pmatrix} + \mu_{i,t} + \vartheta_i + \varepsilon_{i,t} \quad (2)$$

$\varphi(l)$ is a polynomial matrix defined over a lag operator (L), in the following functional form:

$$\varphi(l) = \varphi_1 l_1 + \varphi_2 l_2 + \cdots + \varphi_p l_p \quad (3)$$

The specified PVAR model presents a fixed effects existence problem (ϑ_i), leading to biased coefficients (equation 1). This is because the fixed effects estimator is not consistent, as the individual constant (αi) is correlated with one of the lagged endogenous variables, whether the model is in levels, first differences, or deviations from individual means (Sevestre, 2002). To address this issue, we adopt the procedure of differencing endogenous variables with deviations from future observations' means, also known as the Helmert transformation procedure, to eliminate disturbances and unobservable idiosyncratic factors available for each country (Love & Zicchino, 2006). In this differencing, all integrated variables in the model are transformed as deviations from the future mean.

We assume that the disturbances (structural shocks) are white noise innovations, normally distributed, with a mean of zero and constant variance. This means that observations on $\varepsilon_{i,t}$ are statistically independent and uncorrelated. Since no contemporary variables are included as explanatory variables on the right-hand side, the model takes on reduced form and is thus estimable. Hence, all equations have the same form as they share the same right-hand side variables. This model is linear in both the slope parameters and the lagged variables of the model.

Given that the aforementioned PVAR model has a large number of parameters, its interpretation can be challenging due to the complex interactions and feedback between model variables. Therefore, the dynamic properties of the VAR have been synthesized using various structural analyses, such as (1) Granger causality tests, (2) impulse response functions (which assess the effects of different shocks on the study variables), and (3) variance decompositions (which measure the relative importance of different shocks on the variation of different variables).

4. Results and Interpretations

Before modeling our model, we perform a descriptive analysis of the variables we use.

4.1 Descriptive Analysis

Table 2. Descriptive Statistics for Islamic Banks

	CAR	AP	EL	INFL	LNPIB	PNL	RL	ROA	ROE	SIZE	ZSCORE
Mean	21.2247	52.6228	5.8766	9.5252	8.7764	5.0416	23.0060	1.6251	10.4445	3.3667	24.3797
Median	13.2063	57.0592	6.4771	9.8448	8.4894	3.4029	20.6045	1.3211	11.2094	3.6533	15.9554
Maximum	104.0073	93.3191	9.4285	56.3196	11.2049	119.6921	84.4739	18.63854	59.4807	5.2686	262.1473
Minimum	-1.91937	-11.8180	-0.9652	-25.1298	6.8562	-0.7133	-0.8418	-6.8461	-181.7234	0.2977	-0.9049
Std. Dev.	21.5096	17.7334	2.5384	12.79742	1.3010	7.6242	13.0030	2.1157	14.4373	1.0337	31.3343
Skewness	2.07174	-0.9145	-0.9387	0.4891	0.4376	8.9859	0.8810	1.8126	-5.8173	-1.1009	3.4863
Kurtosis	6.28779	3.9388	3.0259	4.8367	1.8016	124.1010	4.2835	17.6178	77.1327	3.4954	17.8717
Jarque-Bera	498.941	75.3824	62.87417	77.2350	39.2733	267293.7	84.7547	4045.047	100420.1	90.8393	4811.203
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	9084.209	22522.57	2515.195	4076.792	3756.322	2157.838	9846.599	695.5637	4470.266	1440.960	10434.55
Sum Sq. Dev.	197557.6	134280.6	2751.412	69931.50	722.7568	24821.11	72196.76	1911.464	89002.42	456.2911	419246.8
Observations	428	428	428	428	428	428	428	428	428	428	428

Table 3. Descriptive Statistics for Conventional Banks

	CAR	AP	EL	INF	PIB	PNL	RL	ROA	ROE	SIZE	Z_SCORE
Mean	16.8209	45.2791	6.2705	6.39273	9.37443	10.8355	37.6181	7.822824	-680.0698	3.543823	25.29232
Median	13.0872	45.9053	6.2190	5.51968	9.95976	5.25859	26.3919	1.502391	11.41403	3.478052	18.99453
Maximum	99.9547	93.6668	10.6239	150.0007	11.2049	126.7425	937.5934	526.6216	63893.11	5.450156	124.1175
Minimum	-1.3902	-9.8132	-6.07124	-25.9584	6.58856	-34.76739	-49.71461	-67.95659	-511149.0	1.664667	-3.011201
Std. Dev.	13.2107	20.3019	1.51153	13.9474	1.18222	18.2791	81.0124	43.03622	19661.89	0.652535	23.66235
Skewness	3.2070	-0.17581	-0.66186	4.544	-0.07990	4.16953	8.728566	7.772786	-25.51692	-0.015779	1.530985
Kurtosis	16.5448	2.38158	8.98787	45.99979	1.57	22.5703	83.17214	69.06934	662.9289	2.470398	5.848693
Jarque-Bera	12849.2	28.95216	2151.42	110502.8	117.6293	25888.91	385145	263548.6	25063580	16.10265	1000.614
Probability	0.00000	0.00000	0.00000	0.000000	0.000000	0.000000	0.00000	0.000000	0.000000	0.000319	0.000000
Sum	23095.11	62168.32	8609.45	8777.222	12871.10	14877.27	51649.76	10740.74	-933735.8	4865.669	34726.35
Sum Sq. Dev.	239445.3	565497.1	3134.66	266895.5	1917.582	458421.2	9004467.	2541104.	5.30E+11	584.2005	768192.4
Obs	1373	1373	1373	1373	1373	1373	1373	1373	1373	1373	1373

According to Tables 1 and 2, we observe that the standard deviation values of the EL, size, CAR, and Z-score variables are higher for Islamic banks than for conventional banks. Furthermore, both types of banks have a high mean capital adequacy ratio (21.22% for Islamic banks and 16.82% for conventional banks). These results suggest that the capital adequacy ratio for both conventional and Islamic banks is significantly higher than the Basel criteria (8%). The liquidity risk (RL) and credit risk (PNL) variables have a positive mean, indicating high liquidity risk and credit risk among the sampled banks. Thus, these two types of risk are more significant in conventional banks compared to Islamic banks (RL (conv) 37.61% > RL (islam) 23%, PNL (conv) 10.83% > PNL (islam) 5.04%). We also note that liquidity risk is higher than credit risk in all banks. The mean of AP is significant in both types of banks, indicating that the level of lending in the banking sector, whether Islamic or conventional, is higher relative to their assets.

The liquidity gap of banks has a positive average. Therefore, both types of banks do not have sufficient resources to finance their assets.

The size of Islamic and conventional banks has an average of 3.366730 and 3.543823, respectively. Additionally, these banks demonstrate poor performance, with an average economic profitability of only 1.62% in Islamic banks and 7.82% in conventional banks over the selected period.

The standard deviation values of the LR, NPL, ROE, and ROA variables in conventional banks are higher than those in Islamic banks. This indicates that conventional banks are exposed to more risks. The CAR, AP, EL, SIZE, and Z-SCORE variables of Islamic banks have higher standard deviations than conventional banks, indicating that the conventional banking sector outperforms its Islamic counterpart.

We notice that the skewness statistics are significantly greater than zero in absolute value for the entire series, confirming the asymmetrical distribution of our variables. The CAR, Inflation, PNL, RL, ROA, and Z-score parameters in both types of banks have a positive skewness coefficient, indicating a right-skewed distribution, while the remaining variables have negative coefficients, indicating left-skewed distributions compared to the normal distribution.

The kurtosis coefficient for all variables except AP, GDP, and size in conventional banks is greater than 3. This indicates heavy tails on both sides, suggesting the presence of large outliers and a leptokurtic distribution (thicker tails than the normal distribution). In contrast, the distribution of AP, GDP, and size is platykurtic, meaning their tails are thinner than the normal distribution.

As all Jarque-Bera values are very high and exceed the critical value at the 5% level, with probabilities lower than 5%, it is evident that the evaluated variables are not normally distributed. The Jarque-Bera results indicate the attributes of non-linearity in the variables.

4.2 Econometric Analysis

Before studying the impact of credit and liquidity risks on bank stability in both Islamic and conventional banks, it is essential to determine if there is a reciprocal relationship between these two types of risks in the first place to understand their potential contribution to bank instability. To do this, we use a methodology based on the PVAR model to analyze the causality between credit and liquidity risks and their impact on bank stability.

Table 4. Modeling the PVAR Model for Islamic Banks

	RL	AP	CAR	INF	LNPIB	PNL	ROA	ROE	SIZE	ZSCORE
RL(-1)	18.0914	-2.10224	-0.00307	-0.25431	-0.52442	0.67280	1.38962	0.25171	-0.31342	0.59768]
AP(-1)	-0.63735	17.0509	-1.10288	0.14533	-1.33842	0.03542	-0.75750	-0.92113	1.30951	-0.85931
CAR(-1)	-1.11317	-0.11417	13.9587	1.33473	0.06207	-2.04909	-0.10669	-1.98356	-0.20858	2.08676
INF (-1)	-1.09002	0.01427	0.41194	5.21186	-1.52957	1.91579	-0.46316	-0.41284	0.43098	0.31484
LNPIB(-1)	-0.21602	-1.37387	-0.47720	0.11815	17.1550	1.47536	-0.31248	-0.46670	-1.04858	0.28741
PNL(-1)	-0.30444	0.88315	-1.09193	2.73397	-0.22558	19.0328	1.11801	1.08405	0.26417	-0.04113
ROA(-1)	0.49761	0.18433	0.42374	-0.82714	-0.38537	0.67512	5.59473	3.12677	-1.43817	-0.47805
ROE(-1)	-0.24777	0.06867	-0.92230	1.12026	0.99272	-0.92114	4.81408	11.2195	-0.00083	-0.14469
SIZE(-1)	-1.39799	-0.00247	0.52984	0.56147	0.01522	0.71668	0.18801	0.68988	21.1460	0.53611
ZSCORE(-1)	0.88386	-0.48744	-5.40223	-0.13449	-0.09784	1.00590	-0.08473	0.96969	1.84892	5.45032
C	2.11129	-0.60726	-0.26356	1.31672	-0.22578	-1.18470	0.29504	-0.53382	0.36854	-0.99944

Table 5. Modeling the PVAR Model for Conventional Banks

	RL	ROA	ROE	Z_SCORE	PNL	LNPIB	INF	EL	CAR	AP
RL(-1)	35.6034	6.00825	-0.91795	0.72745	-0.96532	-0.26582	-2.33764	-1.27897	2.35235	0.23103
ROA(-1)	2.70792	10.3407	2.70222	-1.37813	2.00470	-0.87176	-0.54127	1.62409	-1.75433	-0.63116
ROE(-1)	0.70556	0.75038	-1.82583	-0.35519	7.52049	0.44555	0.02944	-6.12078	-1.37439	-0.23229
Z_SCORE(-1)	-0.16090	1.47148	-0.55258	21.3142	-0.87861	-0.11870	-0.58236	-0.20524	-3.20392	2.68528
PNL(-1)	-2.27348	-2.46097	8.12467	-0.07319	34.0886	1.22062	0.68029	2.57433	0.08382	0.26465
LNPIB(-1)	0.94287	-0.31034	0.41169	-1.17521	0.00216	43.8755	-11.3630	-1.18151	-0.03140	-2.09842
INF(-1)	1.43023	-0.30070	0.78507	0.52763	0.20724	-2.92987	15.9207	0.93340	-0.29391	0.37239
EL(-1)	-1.15776	-2.44170	0.74212	0.08680	-0.89081	-1.05160	-0.05516	29.7807	0.18180	-0.84427
CAR(-1)	0.78691	-0.81285	0.06838	2.08072	1.47835	0.34283	1.68176	2.46721	31.1042	-1.81762
AP(-1)	-0.92382	-0.67987	0.91336	0.47300	1.03946	-0.90800	-5.06250	-0.19751	-0.92263	41.3471
C	-0.67291	0.40637	0.31943	1.19463	2.54238	0.74512	6.63559	1.45601	1.84303	0.44349

Tables 4 and 5 present the estimated results using the PVAR model regression for both Islamic and conventional banks. If the absolute value of the t-statistic is greater than the critical value of 1.96 or 2, then we conclude that the coefficient is significantly different from zero.

We notice that all the variables in the first equation, exploring the effect of liquidity risk on credit risk, have a t-statistic less than 2, indicating that they are not significant, except for the constant, which has a t-statistic greater than its critical value, meaning the constant is significantly different from zero.

In contrast, in the second equation examining the impact of credit risk on liquidity risk, all variables are not significant except for the CAR variable. Causality between credit risk and liquidity risk is negative and not significant in both equations for conventional banks.

The third equation that examines the relationship between credit risk, liquidity risk, and bank stability in conventional banks shows that all variables are negative and not significant. This finding allows us to conclude that there is no correlation between the two risks and conventional bank stability. Therefore, our hypotheses H2 and H3 are not confirmed.

For Islamic banks, the t-statistic values for all variables in the first equation are lower, allowing us to conclude that these variables are not significant, except for the ROA ratio, which is significant. In the second equation, the constant, the ROE ratio, and the liquidity risk RL are significant (their t-statistic values are higher than the critical value). We also observe a negative relationship between credit risk and liquidity risk in Islamic banks. Hypothesis H1 is not verified.

We observe that the absolute value of the t-statistic for all variables in the third equation, which represents the relationship between the two risks and Islamic bank stability, is less than 2, indicating that the variables are not significant. The causality between the two risks and stability in Islamic banks is negative, meaning that credit risk and liquidity risk do not affect Islamic bank stability. This means that hypotheses H2 and H3 are not confirmed.

Therefore, from a statistical and economic perspective, the results show, firstly, that there is no statistically significant reciprocal relationship between liquidity risk and credit risk, confirming the results of Imbierowicz and Rauch (2014) who found no reciprocal relationship between credit and liquidity risks. This can be explained by investors having incomplete portfolio preferences, or due to firms needing to refinance their debt at maturity and facing increasing credit spreads when market liquidity deteriorated earlier (He & Xiong, 2012c).

The PVAR model shows the absence of a reciprocal relationship between liquidity risk, credit risk, and their impact on bank stability in both Islamic and conventional banks. To confirm this finding, we estimate our regression through additional robustness tests, such as the instant causality Wald-type test in a robustness test for our results. This test is characterized by a test for non-zero correlation between the error terms of the cause and effect variables (Lutkepohl, 2005).

Table 6. Granger Causality/Block Exogeneity VAR Tests for Conventional Banks

Dependent variable: RL			Dependent variable: PNL			Dependent variable: Z-SCORE		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
ROA	73.15388	0.0000	ROA	5.246670	0.2629	RL	1.893126	0.7554
ROE	2.693911	0.6103	ROE	66.00574	0.2629	ROA	2.870132	0.5798
PNL	10.68026	0.0604	RL	18.68603	0.1250	ROE	0.702344	0.9510
LNPIB	4.291176	0.3680	LNPIB	2.971029	0.5627	PNL	1.915921	0.7512
INF	9.899256	0.0422	INF	4.016626	0.4038	LNPIB	4.116541	0.3905
EL	6.485798	0.1657	EL	4.876004	0.3003	INF	2.636779	0.6203
CAR	4.251707	0.3730	CAR	6.903864	0.1411	EL	3.690106	0.4496
AP	1.688370	0.7928	AP	2.712889	0.6070	CAR	9.008510	0.0609
Z_SCORE	1.519502	0.8232	z-score			AP	1.713430	0.7883

Table 7. Granger Causality/Block Exogeneity VAR Tests for Islamic Banks

Dependent variable: RL			Dependent variable: PNL			Dependent variable : Z-SCORE		
E xcluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
PNL	1.963710	0.9230	RL	5.622278	0.3230	RL	0.948341	0.9875
AP	8.212221	0.2230	AP	11.82644	0.6103	AP	1.251491	0.9743
CAR	4.598334	0.5963	CAR	12.40982	0.8232	CAR	6.089289	0.4133
INF	21.11150	0.0018	INF	11.60721	0.0304	INF	4.965278	0.5483
LNPIB	3.012739	0.8072	LNPIB	20.07562	0.3680	LNPIB	1.297090	0.9718
ROA	8.683961	0.1921	ROA	2.010332	0.0422	PNL	0.978128	0.9864
ROE	4.515503	0.6073	ROE	5.066722	0.1657	ROA	2.524588	0.8657
SIZE	8.233932	0.2215	SIZE	14.42143	0.3730	ROE	1.312018	0.9710
ZSCORE	3.161558	0.7883	ZSCORE	5.522280	0.4788	SIZE	2.678602	0.8480

Tables 6 and 7 present the results of the Granger causality VAR tests or Block Exogeneity Wald tests for conventional banks and Islamic banks. We observe that the results of our previous analyses are confirmed. Specifically, the coefficients for liquidity risk and credit risk are not statistically significant in both VAR Granger models, suggesting there is no reciprocal relationship between liquidity risk and credit risk in both types of banks. Therefore, our results indicate that there is no economically significant relationship between liquidity risk and credit risk.

The absence of this relationship in Islamic banks can be attributed to their compliance with Sharia principles, including the prohibition of interest and the sharing of profits and losses, as well as their diversification of tangible assets. Similarly, conventional banks tend to diversify their credit portfolios by offering a variety of loan products to different types of clients and across various industries. This diversification allows them to spread credit risk across a wide range of borrowers, reducing the likelihood of massive losses in their portfolios. As a result, changes in liquidity risk do not necessarily have a corresponding impact on credit risk.

Furthermore, the Granger causality test between liquidity risk (RL), credit risk (PNL), and banking stability did not yield significant results, as the p-values (Prob.*) for RL and PNL (0.7554 and 0.7512, respectively, in conventional banks) are greater than 0.05 (5%). Therefore, we accept the null hypothesis H0 and we conclude that there is no Granger causality between liquidity risk, credit risk, and banking stability in both Islamic and conventional banks.

The combination of Sharia compliance, asset diversification, prudent risk management, and loss-sharing contributes to a reduction in credit risk and liquidity risk, thereby enhancing the overall stability of Islamic banks.

To assess how shocks to economic variables propagate within an economic system, we utilize impulse response functions and variance decompositions.

The following figures present the impulse response functions for control variables (ROA, ROE, GDP, inflation rate, liquidity gap, CAR ratio, and loan assets) concerning liquidity risk, credit risk, and banking stability over ten-year periods for both Islamic and conventional banks.

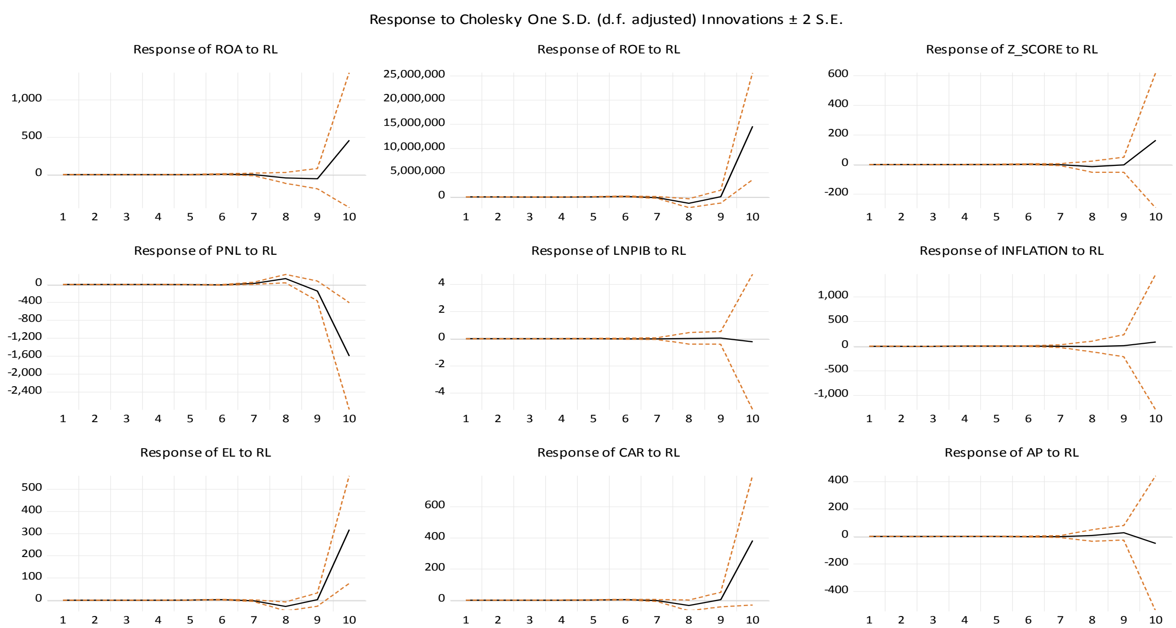

Figure 1. Impulse Response Functions on Liquidity Risk in Conventional Banks

The Figure 1 above illustrates the effects of a shock to liquidity risk on the other variables in the VAR model. It shows that the shock to liquidity risk had a stable effect and then a positive effect starting from the 9th year on the variables ROA, ROE, Z-SCORE, EL, and CAR, and a negative impact on credit risk (PNL). The RL shock has a stable impulse response on the variables GDP and inflation rate. Meanwhile, AP slightly decreased starting from the 10th year.

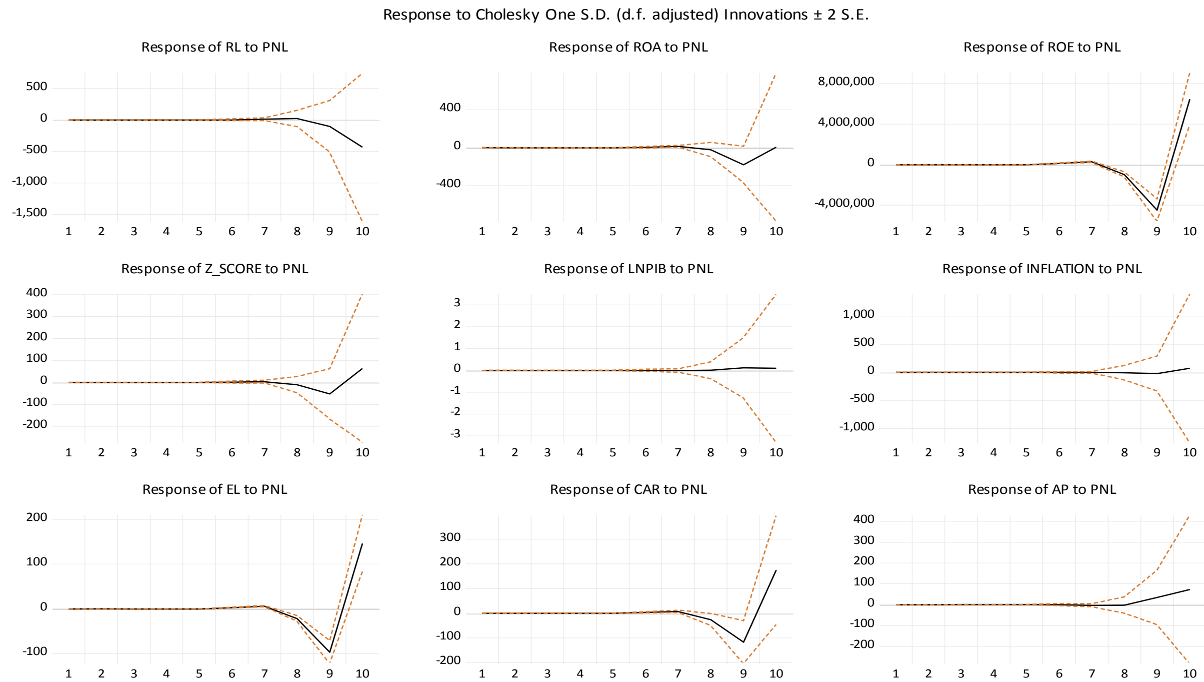

Figure 2. Impulse Response Functions on Credit Risk in Conventional Banks

The Figure 2 above depicts the effects of a credit risk shock on the other variables in the VAR model. It shows that the credit risk shock had a stable effect, followed by a positive effect starting from the 8th year on AP, and a negative impact followed by a positive one starting from the 9th year on ROE, ROA, EL, Z-SCORE, and CAR. The PNL shock has a stable impulse response on the variables GDP and inflation rate. Meanwhile, RL decreased starting from the 9th year.

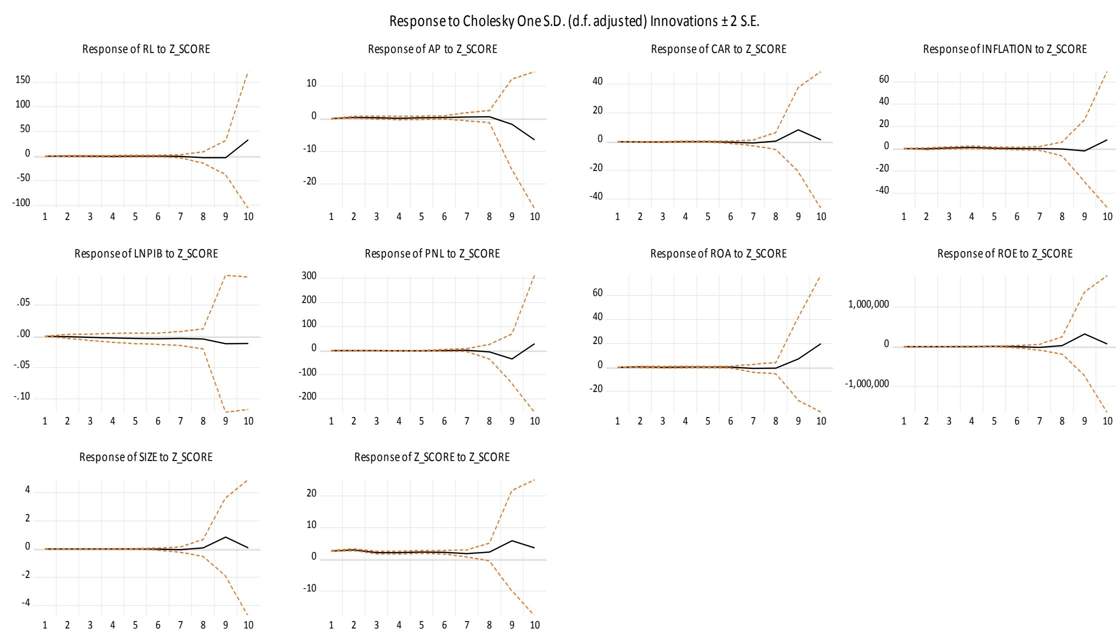

Figure 3. Impulse Response Functions on the Financial Stability in Conventional Banks

The shock to the financial stability of conventional banks has a stable impact followed by a positive effect on RL, inflation rate, ROA, and a negative effect on AP. Additionally, it has a positive and then stable impulse response on CAR and bank size. GDP remains stable. PNL experiences a slight decrease followed by a rapid increase.

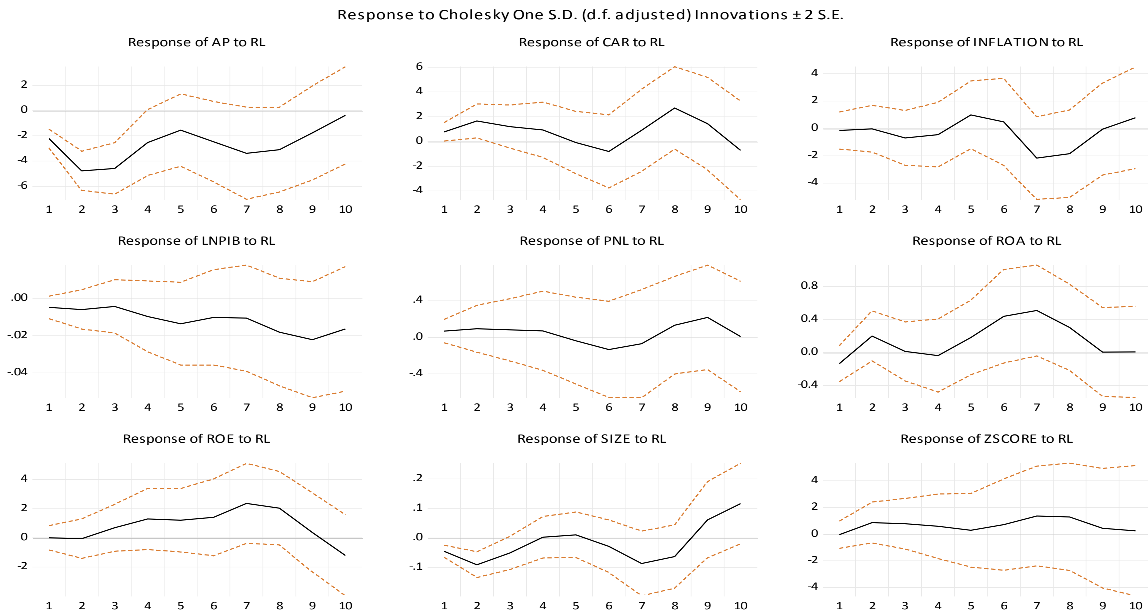

Figure 4. Impulse Response Functions on the Liquidity Risk of Islamic Banks

The Figure 4 shows a negative effect on AP and a positive effect on GDP following a shock to liquidity risk. The RL shock has both positive and negative effect on CAR, inflation rate, PNL, ROE, and bank size. Whereas, it has a positive impact on z-score and ROA.

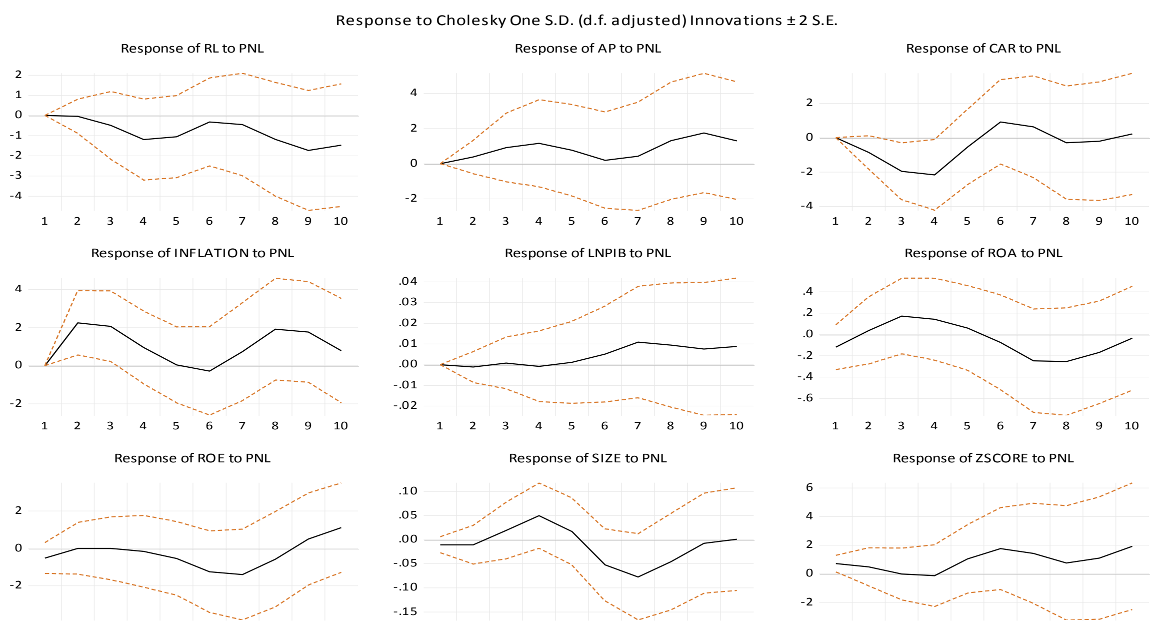

Figure 5. Impulse Response Functions on the Credit Risk of Islamic Banks

The PNL shock has a negative impact on liquidity risk and a positive effect on the z-score.

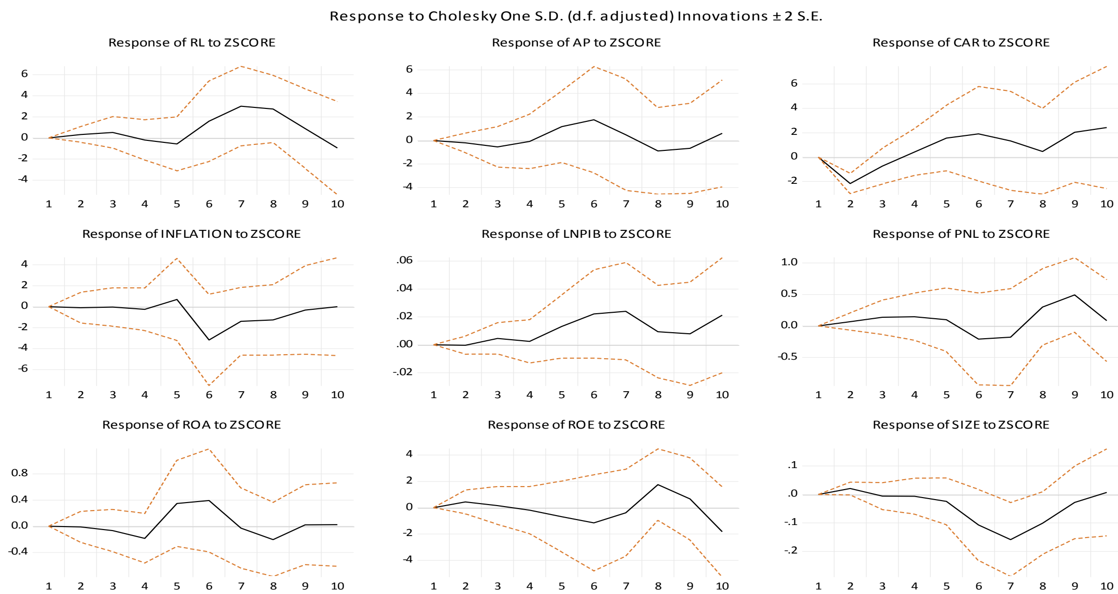

Figure 6. Impulse Response Functions on the Banking Stability of Islamic Banks

The impulse responses to a shock on Islamic banking stability are stable from the first year until the 5th year, then they increase until the 9th year, and afterward, they decrease for liquidity risk. The PNL reacted with a slight increase, followed by a decrease, and starting from the 7th year, it increased again.

In conventional banks, the responses of PNL and z-score to a liquidity risk shock were negative and positive, respectively. This implies that liquidity risk shocks have a negative impact on PNL and a positive impact on the z-score. Shocks on the PNL did not have an impact on liquidity risk and had a negative impact, followed by a slightly positive impact on the z-score. Furthermore, the effect of shocks on the z-score is positive for liquidity risk and slightly positive for the PNL.

In Islamic banks, liquidity risk shocks have a fluctuating effect on the PNL, being positive once, slightly equal to zero, and negative another time. They have a positive effect on the z-score. A negative impact followed by a positive impact on liquidity risk and the z-score, respectively, due partly to the credit risk shock. The responses of liquidity risk and PNL were positive once and negative another time following the z-score shock.

Subsequently, we perform a variance decomposition of liquidity risk, credit risk, and banking stability for Islamic and conventional banks to identify the sources of variation in these variables.

Table 8. Variance Decomposition in Conventional Banks

Variance Decomposition of RL:

Period	S.E.	RL	AP	CAR	INFL	LNPIB	PNL	ROA	ROE	SIZE	Z_SCORE
1	12.75273	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	20.33167	98.63357	0.022913	0.067938	0.111636	0.038105	0.238961	0.743051	0.070562	0.070196	0.003067
3	22.53455	94.44474	0.137380	0.064403	0.104600	0.053427	0.633034	4.170698	0.059425	0.309115	0.023174
4	23.12393	90.58460	0.242832	0.071150	0.306571	0.073055	0.726961	6.669727	0.685777	0.538685	0.100643
5	26.92661	68.04704	0.188803	0.060183	0.230095	0.247646	1.679712	5.695453	23.33360	0.434589	0.082876
6	37.37199	43.03026	0.501115	0.070791	0.281461	0.148101	1.186446	3.065765	51.44618	0.226843	0.043034
7	147.0070	5.413706	0.443396	0.068698	0.054193	0.010941	7.236229	1.021437	85.73140	0.014997	0.005009
8	154.7794	5.997302	0.438974	0.098350	0.175940	0.026576	12.22656	1.551049	79.37707	0.057433	0.050743
9	1796.398	0.703093	0.471712	0.046950	0.001475	0.007159	6.006815	0.623528	92.13710	0.001429	0.000744
10	2410.547	1.521922	0.314930	0.112496	0.061129	0.007518	16.78786	2.188626	78.98179	0.004669	0.019062

Variance Decomposition of PNL:

Period	S.E.	RL	AP	CAR	INF	LNPIB	PNL	ROA	ROE	SIZE	Z_SCORE
1	3.542435	6.624042	0.305915	0.070357	0.026082	0.002418	92.97119	0.000000	0.000000	0.000000	0.000000
2	6.320523	5.997253	0.231637	0.184665	0.081304	0.001051	87.56892	0.562089	5.283657	0.065722	0.023698
3	8.863333	6.744044	0.330270	0.256928	0.045992	0.004808	73.33640	0.999269	18.12167	0.060667	0.099952
4	10.81921	6.313532	0.439641	0.459565	0.218853	0.011690	59.78614	1.782751	30.60235	0.175452	0.210031
5	50.10661	0.764666	0.506506	0.036578	0.043954	0.020973	6.913670	0.476999	91.19672	0.021146	0.018787
6	84.95497	1.426272	0.319712	0.087861	0.108584	0.007456	14.37153	1.915608	81.73625	0.014018	0.012703
7	387.4813	0.558257	0.501809	0.034319	0.011059	0.008955	4.308090	0.415286	94.15248	0.006735	0.003008
8	1454.307	1.046861	0.398239	0.071775	0.009484	0.002236	9.937918	1.095098	87.43638	0.000537	0.001469
9	3480.655	0.371830	0.590700	0.023883	0.016676	0.018727	2.711497	0.237345	96.01362	0.005783	0.009938
10	18526.30	0.905841	0.416288	0.062614	0.004418	0.003635	8.289131	0.922460	89.39457	0.000462	0.000581

Variance Decomposition of Z_SCORE:

Period	S.E.	RL	AP	CAR	INF	LNPIB	PNL	ROA	ROE	SIZE	Z_SCORE
1	3.696070	0.000513	0.046504	49.50249	0.032468	0.256376	0.038905	0.029557	0.004273	0.059452	50.02946
2	5.746765	0.009430	0.096094	52.62069	0.051435	0.122832	0.040362	0.056943	0.029540	0.031874	46.94080
3	6.715895	0.027909	0.070653	54.04941	0.061726	0.118707	0.209064	0.167209	0.491917	0.454072	44.34933
4	7.554066	0.028057	0.056033	53.40682	0.172317	0.125859	0.687854	0.352000	1.824487	0.760101	42.58647
5	9.209779	0.248028	0.116673	44.88376	0.339619	0.085273	0.770955	0.237620	17.70812	0.712305	34.89764
6	15.69689	1.033892	0.235260	19.12804	0.208345	0.029437	6.574786	0.724814	57.84888	0.294772	13.92177
7	31.11747	0.372262	0.506883	5.359735	0.063885	0.032475	2.559286	0.253620	86.89861	0.076263	3.876982
8	179.2258	0.853526	0.426198	0.174324	0.011461	0.005735	8.031468	0.881848	89.48037	0.002350	0.132723
9	221.7084	0.586116	0.589526	0.115644	0.091781	0.027043	6.430121	0.865763	91.12024	0.018487	0.155273
10	2078.976	0.763835	0.452622	0.057606	0.001513	0.005454	6.641000	0.701086	91.37367	0.001146	0.002064

Table 9. Variance Decomposition in Islamic Banks

Variance Decomposition of RL:

Period	S.E.	RL	AP	CAR	INF	LNPIB	PNL	ROA	ROE	SIZE	ZSCORE
1	5.436878	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	10.49507	99.47050	0.112102	0.000715	0.137026	0.012305	0.001648	0.022932	0.000464	0.143493	0.098810
3	11.95539	96.64193	0.137917	0.086785	1.968596	0.035895	0.170589	0.065558	0.280821	0.339033	0.272878
4	12.33378	92.27878	0.406102	1.263856	3.117078	0.390757	1.098351	0.175559	0.657409	0.331740	0.280368
5	12.62983	89.44035	0.387315	2.440928	3.286549	0.373451	1.741236	0.490045	0.667006	0.705816	0.467302
6	14.00940	78.59922	2.730218	4.293361	3.877417	0.594409	1.467751	5.134960	0.567502	1.076484	1.658676
7	16.30952	69.45668	4.693024	6.638764	4.082590	0.485639	1.159530	7.474647	0.439964	0.919384	4.649778
8	17.85584	66.08510	5.180044	7.480889	3.879959	0.887705	1.405639	7.097236	0.376852	1.373268	6.233305
9	18.21297	64.30854	5.418968	7.328020	4.095565	1.288502	2.254844	7.218071	0.525769	1.332451	6.229265
10	18.59269	61.81150	5.215749	7.171025	4.226479	1.393781	2.786137	7.459737	0.621613	3.075066	6.238917

Variance Decomposition of PNL:

Period	S.E.	RL	AP	CAR	INF	LNPIB	PNL	ROA	ROE	SIZE	ZSCORE
1	1.002281	0.420161	9.945279	0.014329	0.257700	0.737684	88.62485	0.000000	0.000000	0.000000	0.000000
2	1.919450	0.334993	8.833076	1.045858	1.339199	0.235422	87.82298	0.002692	0.110600	0.145154	0.130030
3	2.430244	0.313457	6.325631	0.900323	4.142837	1.116806	86.57493	0.008717	0.127985	0.090626	0.398693
4	2.677038	0.321404	5.242225	0.798080	8.145020	2.195984	82.06707	0.048203	0.375319	0.180923	0.625768
5	2.812746	0.310974	4.917551	1.466558	10.28271	2.546816	78.78459	0.115842	0.719608	0.167582	0.687763
6	2.913900	0.506234	4.592943	1.589976	10.76206	3.641174	75.91087	0.229859	1.145759	0.475806	1.145319
7	3.023370	0.526561	4.276163	1.727889	10.74507	5.444127	72.00004	0.290549	1.432544	2.152980	1.404084
8	3.174796	0.641292	4.274081	3.747702	10.59726	6.014060	66.54430	0.603199	1.441426	3.962857	2.173827
9	3.358095	0.979961	5.205734	5.831879	10.11100	6.226275	61.14233	0.878355	1.301970	4.229500	4.092991
10	3.467810	0.919096	5.628991	6.580946	9.937671	7.457886	59.01729	0.824487	1.223119	4.511052	3.899464

Variance Decomposition of ZSCORE:

Period	S.E.	RL	AP	CAR	INF	LNPIB	PNL	ROA	ROE	SIZE	ZSCORE
1	8.041005	0.002732	0.740434	66.25846	0.047083	0.072851	0.773813	0.173878	0.397875	3.514791	28.01808
2	11.11883	0.599821	1.804287	70.98669	0.024767	0.039539	0.591553	0.389971	0.258915	3.328631	21.97583
3	13.11084	0.783486	2.076865	71.64136	0.145001	0.128042	0.425791	0.914714	0.264945	3.279048	20.34075
4	14.50832	0.801354	2.025665	71.13244	0.944705	0.235750	0.356165	1.511530	0.440676	3.019940	19.53178
5	18.07251	0.541094	2.313955	68.18440	1.359041	0.156675	0.561548	2.167251	0.590564	2.408012	21.71746
6	21.77590	0.479073	3.254159	65.19980	2.004561	0.158243	1.039380	2.687781	0.665939	1.905781	22.60528
7	24.42045	0.687222	3.528676	63.76251	3.290784	0.383968	1.161954	2.973429	0.774812	1.668827	21.76782
8	26.34169	0.831344	3.356560	62.84987	5.548694	0.511282	1.081130	3.101941	0.870202	1.626619	20.22236
9	28.70868	0.723537	3.095890	61.65734	7.684328	0.451944	1.054347	3.170846	0.946224	1.732917	19.48263
10	31.34112	0.613390	3.098050	59.54282	9.691053	0.386667	1.260142	3.213841	1.147009	1.599780	19.44724

In the conventional banking sector, the variance decomposition of liquidity risk, credit risk, and banking stability show that liquidity risk attributes 100% of its lagged values for the first year. This decomposition decreases over time. During the second year, liquidity risk is decomposed with 98.63% of its lagged values and the remaining portion attributed to other variables in the VAR model.

The variance of credit risk is decomposed with 92.97% from its lagged values, 6.62% from the lags of liquidity risk, and the remainder from other variables in the model during the first year. The variance of the z-score attributes 50% to its own lags and the rest to other variables.

We notice that liquidity risk is not explained by the lags of other variables during the first year. This decomposition decreases over time. For example, during the second period, liquidity risk is decomposed with 99.47% from its lags and 0.53% from the lags of other variables. Furthermore, the variance of credit risk is explained by 88.82% from its lags, 0.42% from the lags of liquidity risk, and 11.76% from the lags of the other VAR model variables during the first year. During the first period, Islamic banking stability contributed about 28% of its lags.

To determine if there is a relationship between liquidity risk, credit risk, and banking stability in Islamic and conventional banks, we use the Granger causality test. The tables below illustrate the results obtained by the Granger test for Islamic banks and conventional banks.

Table 10. Granger Causality Test for Islamic Banks

Nul lHypothesis:	Obs	F-Statistic	Prob.
PNL does not Granger Cause RL	380	0.25234	0.7771
RL does not Granger Cause PNL		0.83949	0.4327
ZSCORE does not Granger Cause RL	420	1.56412	0.2105
RL does not Granger Cause ZSCORE		0.54120	0.5825
ZSCORE does not Granger Cause PNL	380	0.16991	0.8438
PNL does not Granger Cause ZSCORE		0.02369	0.9766

Table 11. Granger Causality Test for Conventional Banks

Null Hypothesis:	Obs	F-Statistic	Prob.
Z_SCORE does not Granger Cause RL	1230	0.22762	0.7965
RL does not Granger Cause Z_SCORE		0.03148	0.9690
PNL does not Granger Cause RL	1230	1.01035	0.3644
RL does not Granger Cause PNL		6.84075	0.0011
PNL does not Granger Cause Z_SCORE	1230	1.02590	0.3588
Z_SCORE does not Granger Cause PNL		1.26736	0.2819

According to Tables 10 and 11, we observe that all the variables are not significant, indicating a probability greater than 0.05. In the table V, the probability value of RL does not Granger Cause PNL is 0.0011, is smaller than 0.05. Therefore, there is no causality relationship between credit risk, liquidity risk, and banking stability in both Islamic and conventional banks. In fact, there is only a unidirectional relationship from RL to PNL at the 5% significance level within conventional banks.

The Wald test and the Granger test shows similar results. These findings confirm the strong performance of Islamic banks, while conventional banks are also performing well, though to a slightly lesser extent than their Islamic counterparts.

5. Conclusion

Liquidity risk and credit risk are two of the most critical factors for the survival of banks. This study examined these two risks and their impacts on banking stability by using a panel dataset of 110 banks, including 88 conventional banks and 28 Islamic banks, operating in the MENA countries from 2006 to 2021. The independent variables included bank size, return on equity (ROE), capital adequacy ratio (CAR), liquidity gap (EL), ratio of loan assets

(AP), and return on assets (ROA), along with macroeconomic variables such as GDP and inflation rate. The dependent variables consisted of liquidity risk (RL), credit risk (PNL), and banking stability measured by the z-score. The analysis was conducted by using the Panel Vector Autoregressive (PVAR) model. After estimating our models, we observed that there is no significant contemporaneous or time-lagged reciprocal relationship between credit risk and liquidity risk for both Islamic and conventional banks. This lack of significant relationship may be attributed to varying levels of credit and liquidity risks within banks. On the other hand, the negative relationship between these two risks in Islamic banks may also be influenced by governance mechanisms and customer behavior in Islamic banks. The Islamic banking sector employs a multidimensional governance structure, including a Sharia'a supervisory committee, which ensures that all activities comply with ethical standards.

Furthermore, we also found that both types of banks exhibit a negative relationship between liquidity risk and banking stability as measured by the z-score. Generally, Islamic banks tend to have lower liquidity risk compared to conventional banks, which initially enhances the stability of the Islamic banking system. However, lower liquidity risk may lead the bank management to take on more risks to boost profitability, thereby nullifying the initial positive impact and increasing bank instability. Additionally, we also observe that Islamic banks outperform conventional banks in terms of credit and liquidity risk, while conventional banks tend to be more stable. We conducted robustness tests using various methods, including the Wald block causality test and the Granger test, which further support our findings.

To the best of our knowledge, our study is pioneering in terms of empirically uncovering the relationship between liquidity risk and credit risk, as well as their impact on banking stability, with a specific focus on Islamic banks and comparing them to conventional banks. The conclusions we have drawn have significant implications that deserve further in-depth exploration :

The use of the panel autoregressive model (PVAR) to analyze and assess the impact of liquidity and credit risks on banking stability in both Islamic and conventional banks is both significant and innovative. This methodology helps uncover empirical links between these risks and banking stability, providing tangible data to guide risk management and regulatory decisions. Furthermore, our findings support recent regulatory efforts, including the Basel III framework, which place a greater emphasis on the joint management of liquidity and credit risks. The comparative study between Islamic and conventional banks paves the way for a better understanding of the advantages and vulnerabilities inherent in each model, helping policymakers and regulators make informed decisions.

Further consideration could be focused on the impact of socio-economic and political factors on banking risks, providing in-depth insights into the complex mechanisms that shape these institutions. By analyzing how these factors interact with credit and liquidity risks, a better understanding of the inherent risks in both types of banks could emerge, thus contributing enormously to more effective risk management strategies and the promotion of financial stability.

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Authors' contributions

Dr. Ines Hedhili was responsible for the study design, data collection, drafting, and revising of the manuscript.

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The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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