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Early Warning of Bank Failure in the Arab Region: A Logit Regression Approach

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Abstract

The global financial crisis of 2008 taught the biggest lesson of anticipating a financial crisis. The current study aimed to highlight the importance of central banks to build early warning systems to reduce the costs of resolution procedures of weak banks. The data was obtained from published annual reports and balance sheets of 60 commercial banks in the Arab region for the period 2000-2010. Using the logistic regression model to predict the performance of banks or anticipating the possibility of bank failure and build an early warning system, the study identified a few financial indicators such as Capital Adequacy Ratio (CAR); Liquidity (LIQ); Cost to Income Ratio CIR; Return On. Assets (ROA); and Non-Performing Loans (NPL). The impact of the GDP variable on bank`s failure was also determined to capture economic risks. The results showed that financial soundness indicators (FSI) can be used efficiently to predict bank failure, that the variables of ROA and CAR had the greatest impact on the probability of the bank's survival, while no statistical significance was seen for the GDP variable. The paper recommends the importance of the financial stability and banking supervision departments to build early warning systems. The study would provide useful insights to both household and corporate sectors to look for early warning signs that predict the performance of the banking sector in the Arab countries. The FSIs suggested in the study would also play a prominent role in predicting the success or failure of banks in the Arab region.

Keywords: Logit model, Early warning systems, Bank failures, Financial soundness indicators, Central banks, Financial stability.
JEL Classification: G21; G33; C34; C35.

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Contents

Contribution of this paper to the literature
This study provides an opportunity for central banks and researchers to identify the financial, banking, and economic variables that can be used to predict the failure of banks in the Arab region using the logistic regression model, especially since few previous studies have dealt with this issue regarding the Arab region.

1. Introduction

After the global financial crisis in 2008, the supervisory authorities had developed new systems for a continuous monitoring process, represented in the development of early warning systems in order to predict the future conditions of banks, especially those that may suffer from potential challenges in the future. Determining the existence of the problem bank and finding a solution to it is important to ensure the safety of the bank, and to achieve stability in the whole financial system, since banks are the main component of the financial system, and if any bank is liquidated, this will lead to negative effects on the economy in general, which negatively affects financial stability.

Building early warning systems and predicting the occurrence of crises is very important, as it helps to predict the possibilities of bank failure, thus reducing the possibility of banking crises in general, as well as reducing the costs of addressing their effects, with the aim of analyzing the framework and process of identifying the challenges that the bank may face, in addition to the timing and method of intervention. Experience has proven the importance of having a precautionary framework for dealing with banks facing challenges at an early stage. One of the most important challenges facing the supervisory authorities of banks is to ensure the existence of effective supervision at the macro and micro levels and maintain financial stability. Therefore, dealing with banking crises must begin with anticipating the crisis before it occurs, and therefore it is necessary to adopt macro-prudential control in order to identify, monitor and reduce risks to the financial system as a whole.

All methods used in early warning systems depend on statistical and econometric models to predict the performance of the financial sector, whether at the individual level or at the macro level. Depending on micro/macro financial and economic variables, the application of early warning systems requires the existence of a comprehensive and reliable historical database. In the event that a historical database is not available, simpler methods can be used. For example, the performance of "X" bank can be compared through certain indicators with the average value of these indicators in the banking sector as a whole. Examples of early warning indicators that can be used by central banks are the following:

a. The Aggregate Micro Prudential Indicators (AMPIs) can be used by central banks to conduct an analytical framework, according to which indicators are compared at the micro level with the aggregate indicators in order to analyze the soundness or weakness of the banks and their trends. This method is characterized as being easy to apply, and the data used can be provided, using nonparametric statistics.
b. The Heat Map tool is one of the important tools to identify and monitor weaknesses and strengths in the banking sector by displaying them in the form of a risk map, in which a color gradient is used to indicate the quality or weakness of the financial indicators used for each bank.
c. Stress tests are an important tool of risk management that aims to measure the ability of the banking system to withstand financial shocks and high risks, and interest in these tests increased after the global financial crisis 2008. These tests are used by central banks and commercial banks to measure their ability to withstand financial shocks and the high risks that they may be exposed to. These tests aim to assess the financial conditions of banks within stressed scenarios that may occur, and therefore the results of these tests can be used to determine the levels of capital and liquidity that must be maintained by banks to enhance their ability to withstand financial shocks and high risks. These tests have a predictable future dimension in risk assessment using econometric models based on historical information. These tests can also help bank managements understand the bank's situation in a time of crisis.
d. Multiple Discriminant Analysis: Many researchers work to predict the failure of companies using different methodologies. Altman (1968) conducted a Multiple Discriminant Analysis on the data of 66 industrial companies including 33 bankrupt companies, used as financial variables. Altman's study shows that the model used in the study is effective in predicting bankruptcy even two years before the crisis, but with less accuracy if compared to a shorter time. Also, early warning systems were developed for non-linear relationships using logistic regression models, which will be explained later in this study.
e. Financial stability indicators: There is a growing interest of the regulatory authorities in the issue of developing and preparing an indicator of financial stability, recognizing the importance of evaluating systemic risks on a regular basis, and thus assessing the financial stability in general. Many supervisory authorities have developed new systems for the continuous supervision process at the micro and macro levels, represented in the development of financial stability indicators, in order to assess the stability of the financial sector. Where financial stability indicators are considered as an early warning system that reduces the possibility of crises, as well as reducing the costs of addressing their effects.

This study will provide a methodology for developing an early warning system to predict bank failure in the Arab countries based on variables related to the financial soundness indicators for the banks. The study sample included 60 commercial banks in the Arab region during the period (2000-2010).

2. Literature Review

Altman (1968) tried to build an early warning system to anticipate the failure of industrial institutions. The study used the Multiple Discriminant Analysis for 33 bankrupt companies and found that bankruptcy of industrial companies can be predicted using some important financial indicates such as (1) Retained earnings / Total assets, (2) Earnings before interest and taxes / Total assets, (3) Working capital / Total assets, (4) Sales / Total assets, (5) Book value of equity / Book value of liabilities. Martin (1977) showed that it is possible to build an early warning system to predict the performance of banks in the period of 1975–1976, the paper used 25 financial ratios from the Federal Reserve Bank of New York`s database and used Altman methodology (logit analysis) to predict bank failures.

After 1980, the researchers focused on using the logit analysis or the linear logistic regression model by the method of maximum likelihood. They used this method to overcome the defects of the Multiple Discriminant Analysis method (See (Tennyson, Ingram, & Dugan, 1990; Zavgren, 1983)). Zmijewski (1984) tried to predict the American firm`s failure determinants for 1200 firms during the period (1972-1978), by using the Probit model to find the relationship between the financial ratios and the bankruptcies of the industrial firms. The results showed that the net profit to assets ratio, the credit to assets ratio and the assets to liabilities ratio can be used to predict the performance of the industrial firms.

Soo-Wah, Nor, and Yatim (2001) also used eleven financial ratios in Malaysia. The results showed the variables: current asset to current liabilities ratio, sales to current asset ratio, changes in earning after tax percentage have a significant impact on the firm's performance, and they can be used to predict the financial distress. Furthermore, the results showed that the rate of predictive accuracy in this paper at 82,4%. Zhao, Sinha, and Ge (2009) tried to predict the bank failure used logistic regression, neural network, decision tree, and k-nearest neighbor. The results revealed that that feature construction improved classifier performance and that the degree of improvement varies significantly across the methods.

Glezakos, Mylonakis, and Oikonomou (2010) used the logit model to predict the failure of 60 companies (20 bankrupt companies and 40 healthy companies) in Greece, the paper concluded that financial ratios can be used to predict the failure of banks, especially the variables related to capital, liquidity, and profitability indicators. Wong, Wong, and Leung (2010) developed a panel probit model to predict the banking failure probability for EMEAP economies. the results revealed the banking sector is currently more capable to absorb financial and economic shocks similar to those that occurred during the Asian financial crisis. Maricica and Georgeta (2012) attempted to build an early warning system using that financial ratio to provide signals to discriminate between failed and survival firms. Avkiran and Cai (2012) showed that the Data Envelopment Analysis (DEA) can be used to predict the failure of the banking system in the USA, the study used a sample consists of 218 banks. Serrano-Cinca and Gutiérrez-Nieto (2013) applied the Partial Least Square Discriminant Analysis (PLSDA) to predict the failure of the banking system in the USA during the financial crisis period in 2008, The found that the results of using the PLSDA methodology are very accurate compared to the results obtained by Linear Discriminant Analysis and Support Vector Machine.

Zaghdoudi (2013) tried to adopt an early warning system using logistic regression method in order to predict the bank failures in the Tunisian banking sector. The study showed that bank profitability per employee, ability of bank to repay its debt, leverage ratio and the banking operations has a negative impact on the bank`s failure. Erdogan (2016) attempted to develop an early warning system for the banking sector in Turkey using panel data during the period 2002 to 2012. The study used random panel logistic regression versus pooled logistic regression. The return on assets ratio (ROA) was the dependent variable which expressed the bank failure. The study used several financial indicators as an independent variable, such as: Operational efficiency, Equity, Deposit, Asset quality. The study revealed that random-effect logistic regression was the best prediction performance. Momparler, Carmona, and Climent (2016) applied the boosted classification tree methodology to anticipate the bankruptcy failure of 155 banks in Europe, the paper covered the period 2006–2012 using 25 financial ratios. The results indicated that there is a positive relationship between the assets, non-operating income, and loans to deposits, and the bank failure; conversely, the results revealed that there is a negative relationship between the Interbank ratio the lower the bank failure.

Barboza, Kimura, and Altman (2017) used machine learning models to predict the failure of more than 10,000 North American firms, and compared their performance with results from neural networks, logistic regression, and discriminant analysis. They covered the period from 1985 to 2013. The study used the machine learning techniques to enhance the accuracy of the prediction; furthermore, they attempted to find the bankruptcy determinants using Altman's Z-score. They used six financial indicators which were previously used in Carton and Hofer (2006); furthermore, they added new variables, such as change in price-to-book, the operating margin, number of employees , change in return-on-equity, and growth measures related to assets, sales, as dependent variables. The results showed that Machine learning models had more accuracy in relation to the other mentioned models, while the machine learning technique related to random forest, and the logit regression and the discriminant regression led to 87%, 69% and 50% accuracy, respectively. The study found that the results become more accurate when the additional variables are included. Kapinos and Mitnik (2016) found that the top-down approach to stress testing banks in the USA can be used to examine the banks solvency.

Cleary and Hebb (2016) examined the failures of 132 American banks during the period 2002–2009 using discriminant analysis. The results showed that two most important variables to predict the bank`s failure were related to capital and credit quality, in addition to the profitability variables. The paper revealed that the model can easily be applied to many firms in order to predict their performance, and the model can distinguish between healthy and distressed banks. Chiaramonte, Liu, Poli, and Zhou (2016) used Z-score to predict the failure of the commercial banks in the USA, the paper covered the period from 2004 to 2012, the paper revealed that the Z-score can be used to predict 76% of bank failures, the results showed that this percentage will not be increased if an additional set of other banks and macro level variables will be added.

Bongini, Iwanicz-Drozdowska, Smaga, and Witkowski (2018) tried to predict the banking system failure using Z-score and CAMELS indicators for 20 countries in Europe during the period 1995-2014, the results showed that the predictive power of the Z-score was weak.

Cheong and Ramasamy (2019) used the logistic regression to predict the performance of 536 failed and non-failed banks in the USA, the results showed that the capital adequacy ratio (CAR) and the return on average equity (ROE) have a negative on the probability of failure. In other words, the paper showed that banks that have higher levels of financial solvency and operational efficiency have a lower probability of bankruptcy. On the other hand, the results revealed that ratio of net loans to total assets, credit growth and impaired loans have a positive relationship with the probability of failure. Shrivastava, Jeyanthi, and Singh (2020) developed an early warning system for the Indian banks during the period (2000-2017), the paper used bank specific variables, market variables and economic variables. The paper applied Synthetic Minority Oversampling Technique (SMOTE) and Lasso regression to mitigate the redundant features from the failure predictive model, then the paper applied some techniques to avoid the bias and overfitting compared to the logistic regression, this approach will lead to get the best predictive model

Obeid (2021) tried to build an early warning system for the Arab banking sector using the logistic regression model. The study covered the period 2005-2015 to predict the bank`s failure for 40 banks in the Arab region. The financial indicators such as capital adequacy ratio, assets quality, profitability were used to predict the bankruptcy in the Arab banking sector. The study used also the GDP variable to capture the impact of economic risks on the bank`s performance. The study revealed the ability of the financial soundness indicators to predict bank bankruptcy. On the other hand, the results showed that there was no significant statistical relationship between the GDP and the bank`s performance.

Messi, Kenny, and Ogren (2021) tried to analyze the Swedish experience of the international crisis of 1907, the paper showed that the structure of the banks' asset played a more significant role in their subsequent fate. The results revealed that the non-performing loans and lending against equities variables the most important banking indicators which can be used to predict of crisis. These variables significantly affected the lifespan of Swedish banks in the aftermath of the 1907 crisis.

3. Model and Data

This paper attempted to build an early warning system to examine the determinants of bank failure in the Arab region, based on the financial soundness indicators. The impact of the GDP variable was also tested on bank`s failure to capture the economic risks. The data was obtained from published annual reports and balance sheets of banks from the commercial bank's websites and the databases of the capital market authorities in the Arab countries during the period (2000-2010), while we obtained the GDP data from the Arab Monetary Fund database. The definitions of the independent variables used in this paper to predict the bankruptcy of the banking system in the Arab region are shown in Table 1, while the dependent variable takes a dummy value of zero or one based on the bank's failure or survival, as clarified later in section four:

Table 1. Definition of independent variables.

Variables	Variables abbreviation	Definition	Previous studies which have used the variable to predict the probability of failure
Capital Adequacy Ratio	CAR	(Tier 1+ Tier 2 capital)/Risk-weighted Assets)	Cleary and Hebb (2016); Erdogan (2016); Cheong and Ramasamy (2019); Obeid (2021)
Cost-Income Ratio	CIR	Total administrative expenses/Total annual income	Zaghdoudi (2013); Cheong and Ramasamy (2019); Obeid (2021)
Non-performing loans	NPL	Total non-performing loans/Total loans	Glezakos et al. (2010); Cleary and Hebb (2016); Erdogan (2016); Messi et al. (2021)
Return on Assets	ROA	Net income/ Total Assets	Zmijewski (1984); Cleary and Hebb (2016)
Liquid Assets	LIQ	Liquid assets (Cash and short-term assets)/Total assets	Glezakos et al. (2010); Zaghdoudi (2013); Obeid (2021)
Gross Domestic Product	GDP	The real gross domestic product growth rate	Kadri and Mayes (2009); Obeid (2021)

Regarding the expected relationship between the independent variables and the probability of bank`s failure (dependent variable), it is expected that the financial solvency of the bank has an inverse relationship with the possibility of bankruptcy, as the high capital adequacy ratio (CAR) reduces the chances of the bank defaulting, it is known that capital adequacy increases the bank's ability to absorb potential shocks (Obeid, 2021). As for the cost-income rati0 (CIR), it is expected that it has a positive relationship with the possibility of bankruptcy of the bank, as the increase in expenses consumes the bank's liquidity and indicates a decrease in the operational efficiency of the bank (Obeid & Adeinat, 2017). Regarding non-performing loans, it is expected that it has a positive relationship with the possibility of bankruptcy of the bank, as the increase in the percentage of non-performing loans without adequate provisions leads to a decline in the quality of the credit portfolio, and thus may expose the bank to bankruptcy risks if no corrective plans and actions are put in place (Glezakos et al., 2010).

As for the return on assets (ROA) variable, it is expected to have a negative relationship with the probability of bank bankruptcy, as the bank's generation of profits indicates its operational efficiency, and profits enhance capital bases and enhance the confidence of the bank's customers, thus reducing the possibility of bank default (Obeid & Adeinat, 2017).

As for liquid assets, it is expected to have a negative relationship with the probability of bank bankruptcy, as the presence of high levels of liquid assets enhances the bank's ability to meet its obligations and enables it to employ its liquidity with less risks, thus reducing the chances of bank bankruptcy (Zaghdoudi, 2013). Finally, as for the GDP variable, it is expected to have a negative relationship with the possibility of bank bankruptcy, since the stable economic environment encourages investors to borrow from banks, as well as may increase the income of the individual and corporate sectors, which will positively reflect on the quality of the credit portfolio, and thus improve financial positions for banks (Kadri & Mayes, 2009; Obeid & Awad, 2018).

4. Econometric Methodology

The current study used the logit regression approach by the method of maximum likelihood. The model adopted the following formula:

$$\ln\left(\frac{P_{it}}{1-P_{it}}\right) = Z_{it} = \beta_0 + \beta_1 CAR_{it} + \beta_2 CIR_{it} + \beta_3 NPL_{it} + \beta_4 ROA_{it} + \beta_5 LIQ_{it} + \beta_6 GDP_{it} + \varepsilon_{it} \quad (1)$$

$i = 1, 2, \ldots, N, \; t = 1, 2, \ldots, T$

$$P_{it}(Y|X) = \frac{1}{1+e^{-Z_{it}}}, P \in [0,1] \quad (2)$$

Where i refers to bank at time; t, Z_{it} refers to the linear regression which is obtained from the following equation:

$$Z_{it} = \beta_0 + \beta_1 X_{i,t-k} \quad (3)$$

X_i is a vector that refers to financial and economic variables that will be used to predict the banking sector failure, CAR_{it} is the capital adequacy ratio of the bank, CIR_{it} is the operational efficiency (cost income ratio), NPL_{it} is the credit risk (non-performing loans), ROA_{it} is the profitability indicator (return on assets), LIQ_{it} is the liquid assets ratio, and GDP_{it} is the real gross domestic product growth rate, and ε_{it} is the disturbance term. P_{it} is the probability of (Y_i=1) in case the bank (i) is at risk of bankruptcy, and the probability of (Y_i=0) for the viable bank with low risk bankruptcy.

The logit model is considered as one of the most applied approaches which predicts the failure of banks (See (Demirguc-Kunt & Detragiache, 1998; Obeid, 2021)). We analyzed the factors which explained the banks bankruptcy in the Arab world.

This paper used the financial soundness indicators to predict potential failures (See (Altman, 1968; Jagtiani, Kolari, Lemieux, & Shin, 2002; Obeid, 2021)). Back to Equation 3, the binomial regression was used in the logit model, we estimated the probability of bankruptcy or failure P(Z). To predict the probability of survival (Y = 0) or failure (bankruptcy) (Y = 1), we used the following logistic model:

$$P_{i,t}(y) = \begin{cases} P(Z) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_{i,t-k})}}, & y = 1 \\ 1 - P(Z) = 1 - \frac{1}{1+e^{-(\beta_0+\beta_1 X_{i,t-k})}}, & y = 0 \end{cases} \quad (4)$$

Where:

$P_{i,t}$: Probability that bank (i) bankruptcy at time (t), $P \in [0,1]$.

X_i: Vector which contain the variables that will be used to predict bankruptcy of bank (i).

Z_{it}: Linear regression extracted from vector X_i, $Z \in (-\infty,\infty)$.

k: The year before the bankruptcy period.

e: Euler's Number.

β: Vector contains the regression`s coefficients.

The generalized linear method was used in order to calculate the scores (Nelder & Wedderburn, 1972). Then, we used the Lagrangian`s maximum likelihood function to obtain the parameters β_d as following:

$$\text{Max } L(Y|X, b) \quad (5)$$

Next step, we solved the following equation to find the values of the intercept and β `s:

$$L(Y|X, b) = P(Y|X), \text{where: } P(Y|X) = \prod_{j=1}^{n} [P_i^{Yi}(1 - P_i)^{1-Yi} \quad (6)$$

So:

$$\text{Log } LP(Y|X, b) = \prod_{j=1}^{n} [Y_j \log(\frac{1}{1+e^{-(\beta_0+\beta_1 X_{i,t-k})}}) + (1 - Y_j)\log(\frac{1}{1+e^{-(\beta_0+\beta_1 X_{i,t-k})}})] \quad (7)$$

Where:

P: The probability of the bankruptcy of bank (i) at the time (t), $P \in [0,1]$.

X_i: Vector contains the variables to be used to predict the bankruptcy of bank.

k: The year before the bankruptcy period.

β: Regression`s Coefficients.

Final step, we used the Akaike Information Criterion (AIC), this helped to choose the most important performing explanatory variables to predict the bankruptcy of bank as following:

$$AIC = -2LOGL + 2P \quad (8)$$

Where:

L: The maximum likelihood of the fitted model.

P: The number of estimated parameters.

5. Analysis of the Results

5.1. Descriptive Analysis

The descriptive data of the explanatory variables are shown in Table 2, taking into account that some variables have reached zero as a minimum value due to the bank`s failure in a specific period of time (such as: CAR, LIQ, and CIR), while the minimum value of ROA reached about -4.5%, and this value mainly indicates high operating losses and/or poor risk management and/or excessive risk-taking that is not based on an accurate assessment of the borrowers.

Regarding the NPL ratio, the minimum value reached about 1.5%, which indicates an efficient credit risk management. As for the maximum values for the study variables, the value of CAR reached about 20.3%, which indicates the ability of bank to absorb and withstand financial and economic shocks, but at the same time the high ratios of CAR may affect negatively on the bank`s operational efficiency, because the bank may exaggerate in not granting credit. Regarding the LIQ variable, the highest value reaches 93.9%, and this indicates the ability of the banking system to fulfill its obligations.

Table 2. Summary statistics of the variables.

Descriptive data	CAR	LIQ	CIR	ROA	NPL
Mean	0.14	0.58	0.68	0.01	0.07
Median	0.16	0.65	0.63	0.01	0.07
Maximum	0.20	0.94	1.33	0.02	0.16
Minimum	0.00	0.00	0.00	-0.05	0.02
Std. Dev.	0.05	0.28	0.29	0.01	0.04
Skewness	-1.17	-0.75	0.38	-2.10	0.54
Kurtosis	3.66	2.43	2.65	7.81	2.21
Jarque-Bera	16.13	7.06	1.93	111.89	4.88
Probability	0.00	0.03	0.38	0.00	0.09
Observations	660	660	660	660	660

Note: CAR: Capital Adequacy Ratio; LIQ: Liquidity; CIR: Cost to Income Ratio; ROA: Return On. Assets; NPL: Non-Performing Loans.

Regarding the cost to income ratio, the highest value has reached about 133%, and this may indicate a vulnerability in the operational efficiency. This value is often seen in weak banks that suffer in their financial positions. As for the ROA variable, the highest value is seen 2.1%, and this gives a good indication of the efficiency of generating profits from assets. Regarding the NPL ratio, which reached 16%, it shows a weakness in credit risk management, and this may lead to a high possibility of bank`s bankruptcy. At this stage, the role of central banks is very important, they should put a comprehensive corrective plan for these banks to avoid reaching further financial deterioration.

5.2. Bank Failure Prediction

Table 3 shows the results of estimating the logistic regression equation. It must be emphasized that the parameter values provide evidence of the relationship between the independent variables and the probability of the bank's survival (the dependent variable), and not the size of the effects. The results showed that all banking variables were statistically significant, while it was not proven whether there is any relationship between GDP growth and bank bankruptcy. However, it must be emphasized the importance of taking economic risks into account when measuring the risks of the financial system (Obeid & Awad, 2018). With regard to banking variables, the results showed that a high percentage of NPL has a negative relationship with the probability of the bank's survival, meaning that a high percentage of NPL may lead to a higher probability of bank failure, especially in the absence of sufficient provisions at the bank. This result supports the importance of adopting the IFRS9 standard, which included the importance of banks' building provisions towards non-performing and performing credit. This further enhances the bank's strength (Obeid, 2022). About the capital adequacy ratio (CAR), the results showed a positive relationship with the probability of the bank's survival, as the high CAR enhances the bank's ability to withstand potential financial shocks, and this explains the growing interest from the Basel Committee on Banking Supervision in improving the quantity and quality of banking sector capitals, as well as building capital buffers (such as CCyB, CCoB and DSIBs buffer), in accordance with the requirements of Basel III.

As for the ratio of liquid assets to total assets, it was associated with a positive relationship with the probability of the bank's survival, as maintaining good liquidity levels enhances the solvency of the bank and its ability to meet its obligations. It is worth noting that the Basel requirements focused on enhancing the ability of banks to provide the necessary liquidity to meet short and long-term obligations, through the liquidity coverage and net stable funding ratios. As for the return on assets (ROA) variable, as expected, it was associated with a positive relationship with the probability of the bank's survival, as the generation of profits gives evidence of enhancing the operational efficiency of the bank. Finally, the results showed that there is a negative relationship between the percentage of operating expenses (CIR) and the probability of the bank's survival, as the increase in operating expenses indicates the weakness of the bank's management. This may incur losses that affect its financial position, and thus increases the possibility of bank failure. The cost to income ratio (CIR) is one of the most important determinants of operational efficiency (Obeid & Adeinat, 2017).

Table 3. Logistic regression results.

Variables	Estimate	P-Value
CONSTANT	-9.377**	0.035
NPL	-0.821***	0.000
CAR	0.142**	0.022
LIQ	0.087**	0.069
ROA	0.423*	0.098
CIR	-0.087**	0.018
GDP	0.042	0.609
McFadden R-squared	0.8256	
-2 Log likelihood	54.061	
LR statistics	235.039	
P-Value	[0.000]	

Notes: The values in brackets are the p-values of the tests. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.
CAR: Capital Adequacy Ratio; LIQ: Liquidity; CIR: Cost to Income Ratio; ROA: Return On. Assets; NPL: Non-Performing Loans; GDP: Gross Domestic Product

Regarding the size of the impact of the logistic model variables on the probability of the bank's survival, it is noted from Table 4 that the rate of return on assets (ROA) and then the capital adequacy ratio (CAR) are the most influential, but in general, Table 4 showed the importance of the role of financial soundness indicators in predicting the bank's performance in terms of success or failure.

Table 4. Odd Ratio for the significant variables.

Variables	Odd Ratio
CONSTANT	0
NPL	0.44
CAR	1.15
LIQ	1.09
ROA	1.53
CIR	0.92

Note: CAR: Capital Adequacy Ratio; LIQ: Liquidity; CIR: Cost to Income Ratio; ROA: Return On. Assets; NPL: Non-Performing Loans.

Finally, Table 5 shows the Expectation-Prediction Evaluation for Binary Specification (Success cut-off point=0.5) while Table 6 shows the Goodness-of-Fit Evaluation for Binary Specification, the Andrews Statistic test has a value of 231.2, while the Hosmer-Lemeshow test has a value of 51.6. The HL test is used for risk prediction models, it evaluates how the data fits the model the accuracy of the prediction (Hosmer, Lemeshow, & Sturdivant, 2013).

Table 5. Expectation-prediction evaluation for binary specification.

Equation: EQ01						
Success cutoff: C = 0.5						
Results	**Estimated Equation**			**Constant Probability**		
	Dep=0	**Dep=1**	**Total**	**Dep=0**	**Dep=1**	**Total**
P(Dep=1)<=C	59	1	60	0	0	0
P(Dep=1)>C	1	599	600	60	600	660
Total	60	600	660	60	600	660
Correct	59	599	658	0	600	600
% Correct	98.33	99.83	99.70	0.00	100.00	90.91
% Incorrect	1.67	0.17	0.30	100.00	0.00	9.09
Total Gain*	98.33	-0.25	8.64	-	-	-
Percent Gain**	98.33	NA	95.00	-	-	-
Results	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	58.32	1.68	60.00	3.64	56.36	60.00
E(# of Dep=1)	1.68	598.32	600.00	36.36	563.64	600.00
Total	60.00	600.00	660.00	60.00	600.00	660.00
Correct	58.32	598.32	647.64	3.64	563.64	567.28
% Correct	97.20	99.72	98.13	9.09	90.91	83.47
% Incorrect	2.80	0.28	1.77	90.91	9.09	16.53
Total Gain*	86.71	8.67	15.77	-	-	-
Percent Gain**	95.38	95.38	95.38	-	-	-

Note: *Change "%Correct" from default (constant probability) specification.
**Percent of incorrect (default) prediction corrected by equation.

Table 6. Goodness-of-Fit evaluation for binary specification.

Andrews and Hosmer-Lemeshow								
Grouping based upon predicted risk (randomize ties)								
	Quantile of Risk		**Dep=0**		**Dep=1**		**Total**	**H-L**
No.	**Low**	**High**	**Actual**	**Expect**	**Actual**	**Expect**	**Obs.**	**Value**
1	2.E-06	0.705	54	54.72	12	12.28	66	1.51
2	0.734	0.995	6	6.49	60	62.51	66	4.35
3	0.996	0.998	0	0.13	66	65.87	66	3.73
4	0.998	0.999	0	0.06	66	65.94	66	5.86
5	0.999	0.999	0	0.04	66	65.96	66	6.03
6	0.999	0.999	0	0.03	66	65.97	66	6.02
7	0.999	0.999	0	0.02	66	65.98	66	6.01
8	0.999	0.999	0	0.01	66	65.99	66	6.01
9	0.999	0.999	0	0.01	66	65.99	66	6.00
10	0.999	1.000	0	0.00	66	65.99	66	6.00
Total			60	61.51	600	602.49	660	51.56
H-L Statistic			51.56		Prob. Chi-Sq(8)		0.00	
Andrews Statistic			231.21		Prob. Chi-Sq(10)		0.00	

6. Conclusion and Policy Recommendations

This paper attempted to build a logistic model to predict the performance of the banking sector in the Arab countries, with the aim of providing early warning tools to central banks. Such a proactive step would enable them to anticipate the performance of banks, and thus avoid incurring costs to address any risks that may worsen any situation of crisis. When a bank faces a particular crisis, it must deal with the crisis by predicting it much before it occurs. This study showed that banking variables had a statistically significant importance and could be used in predicting the occurrence of the crisis. The study also showed that the rate of return on assets (ROA) had the most important role in predicting the crisis, followed by the capital adequacy ratio (CAR), and the liquid assets to total assets ratio, costs to income ratio (CIR), and non-performing loans (NPL) to total loans, respectively. As for the economic variables, they had no statistically significant impact on the banking performance. It should also be noted that the effect of the ratio of non-performing loans to total loans, and the ratio of cost to income ratios had a negative impact on the banks' performance (e.g., increased probability of bank failure), while the relationship was positive for the other remaining variables (decreased probability of bank failure).

This paper focused on the importance of central banks to build early warning systems for the banking sector, which may reduce the costs of resolution procedures towards the weak banks. In this paper, a logistic regression model was used to predict the performance of banks or anticipating the possibility of bank failure in the Arab region. Accordingly, the paper recommends the importance of the financial stability and banking supervision departments in central banks to build early warning systems for the banking sector. This will help continue to enhance the resilience of the banking sector, apply the requirements of Basel and International Financial Reporting Standard No. 9, and strengthen the banking crisis management system. In this context, early warning systems can be built using a set of variables that depends on the financial soundness indicators of or the "CAMELS" classification system for the banking system. Itis also possible to add some economic variables in order to capture economic risks as they may play a role in the performance of the banking sector. This study also showed that financial variables played a more important role in predicting bank bankruptcy, but this did not mean neglecting economic variables in predicting bank failure, when building econometrics models or early warning systems that predicted its performance.

Finally, the findings of this study support the findings of Obeid (2021) about predicting the performance of the banking sector in the Arab countries using logistic regression models, as the mentioned study concluded that financial soundness indicators (FSIs) have the most prominent role in predicting the failure of banks in the Arab region, while there is no impact of the GDP variable on the failure of banks. However, as we mentioned earlier, the impact of economic risks must be constantly evaluated when predicting the failure of banks, as economic conditions may have indirect and/or direct effects on the performance of banks. In the event of an economic crisis, this may lead to a decline in cash flows to the household and corporate sectors, which may lead to a rise in bank default rates. This might increase credit risks which might prompt central banks to take a set of stimulus measures for the individual sectors and companies with the aim of preventing them from defaulting on the one hand, and preserving the financial sector on the other.

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