

E-ISSN: 2469-4339

Management and Economics Research Journal, Vol. 6, Iss. 2, Pgs. 9, 2020

Original Research Article

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Stress Testing for Credit Risk Exposure in Islamic Banks

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Received: Jul 10, 2019; Accepted: Jan 25, 2020

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Citation: Mohammed FA, Onour IA. 2020. Stress testing for credit risk exposure in Islamic banks. Management and Economics Research Journal, 6(2): 990010. <https://doi.org/10.18639/MERJ.2020.990010>

Abstract

In this study, we investigate the link between default loans and macroeconomic and bank-specific variables to assess exposure of Islamic banks to credit risks, and then design stress testing scenarios to assess the banking system's resilience to adverse shocks. The results suggest that credit risk exposure of Islamic banks in Sudan is mainly affected by bank-specific variables, which include changes in total assets, total deposits, and total loans; all of them have a negative and significant impact on the probability of default loans. The study also indicates that the macroeconomic variables, which include growth of domestic product, change in exchange rate premium, and change in money supply, have positive but insignificant effects on the risk of default loans. The study concludes by pointing out that the Islamic banking system in Sudan is more vulnerable to bank-specific risk exposure rather than macroeconomic indicators.

Keywords: Credit risk; Islamic banks; Stress testing.

1. INTRODUCTION

Stress tests are a very important tool for assessing the ability of financial institutions to counterbalance the influence of large shocks on their capital. As a result of the world's biggest financial crisis since the Great Depression, there is an increasing interest in stress-testing financial intermediaries to assess their capital needs in the event of large but plausible shocks (Shijaku and Ceca, 2011). However, central banks have a significant task, either by setting basic standards and directing stress tests at the micro level or designing them to assess the financial stability associations of macroeconomic developments and systematic risk. Stress tests are a useful aid in evaluating the stability of banking systems. They allow a forward-looking analysis and help to adopt a consistent approach in detecting the possible risks, which might face the banking system as a whole (Neelakantaiah, 2016). They can capture the impact of exceptional but plausible events on such portfolios; moreover, they could test if the capital cushion is appropriate under stress situations, and also present advance-looking hints in the capital assessment process.

Among the various risks the banking sector faces, the credit risk is the most important source of insolvency problems for banks (Buncic and Melecky, 2013; Papadopoulos and Sager, 2016). Credit risk is the potential for losses from borrower defaults or nonperformance on a contract. Stress tests can be used to assess the various risks the banking sector could face including the credit risk. Credit risk management is practically used by banks to mitigate losses by understanding the adequacy of the bank's capital and loan loss reserve at any given time.

The worldwide financial crises put credit risk management into the supervisory spotlight, which demands more transparency. The new Basel III regulations create a bigger regulatory burden for banks. Without a careful risk assessment, banks have no way of knowing whether their capital reserves exactly reflect risks or whether loan loss reserves sufficiently conceal potential short-term credit losses.

The current study focuses on how to develop a framework that stress tests the exposure of credit risk in the banking system, to assess the vulnerability of the banking sector toward exceptional but plausible shocks, and how to ensure that the bank's risk-weighted credit exposures are resilient to adverse financial shocks. The study focuses on the following issues:

- I. Assessing exposure of the full-fledged Islamic banking system to credit risk.
- II. Assessing the financial system's resilience to adverse financial shocks.

The importance of credit risk stress tests is to offer information about the performance of the banking system under any exceptional but plausible shocks. This could help policymakers evaluate the banking system's vulnerabilities to these shocks. Moreover, in most banking systems, credit risk is the key risk that existing models are most in need of strengthening (Čihák, 2007).

The main objective of the study is to develop a framework that stress tests the exposure of credit risk in the Islamic banks in Sudan. This is done by developing a model that describes the links between the default loans and macroeconomic and bank-specific variables, and then designing a stress-testing scenario and assessing the financial system's resilience to adverse shocks.

2. LITERATURE REVIEW

Revolutionary work in the area of modeling credit risk is the effort by Altman (1968). He uses the discriminant analysis technique to model credit risk. A large set of studies find that credit risk is, in general, driven by idiosyncratic and systemic factors (Bangia *et al.*, 2002; Bonfim, 2009; and Jiménez and Saurina, 2004). The macroeconomic effects are very important in assessing the default probabilities. Instead, there is also a strong reverse effect of credit risk on macroeconomic activity. Gilchrist and Zakrajšek (2012) realize that the movement of economic activity could be explained significantly using the level of credit risk.

According to Čihák (2007), there are three basic groups of approaches to modeling credit risk as part of stress tests. First, there are mechanical approaches (typically used when there are insufficient data or if shocks are different from past ones). Second, there are approaches based on loan performance data (e.g., probabilities of default, losses given default, nonperforming loans [NPLs], and provisions) and regressions (e.g., a single equation, structural, and vector auto regression). Third, there are many approaches built on data from the corporate sector (e.g., leverage or interest coverage) and probably on data from the household sector.

Moreover, Foglia (2009) has identified two approaches for credit risk modeling. These are listed out below:

1. Models based on loan performance in which the key dependent variables are the NPL ratio, the loan loss provision (LLP) ratio, and historical default frequencies.
2. Models based on individual borrowers' data, where in this approach the credit risk satellite model on individual borrowers' data is estimated. However, the model specification may also include macrofinancial data as explanatory variables. In case no macroeconomic variables are incorporated, to link the macrofinancial variables to borrower-specific data, an additional satellite model may be used.

Čihák (2007) summarizes a wide range of contributions, which tried to link credit risk to macroeconomic variables using econometric models. For example, Pesola (2005) presents an econometric study of macroeconomic determinants of credit risk and other sources of banking fragility and distress in the Nordic countries, Belgium, Germany, Greece, Spain, and the United Kingdom from the early 1980s to 2002. An even broader cross-country analysis is presented in IMF (2003). For the Australian banking sector, Boss *et al.* (2006) provide estimates of the relationship between macroeconomic variables and credit risk.

Melecky and Podpiera (2010) add to Foglia's (2009) summary of the credit risk stress-testing practices developed in selected central banks, which include the structural econometric model; vector autoregressive

model; and the statistical approach, a judgmental approach that is used in cases when statistical or econometric models are not capable of producing appropriate stress scenarios. Their approach is often employed by developing countries' central banks consequent to the lack of historical data for estimation of macroeconomic models. However, the model specification may also include macrofinancial data as explanatory variables.

3. DATA AND SAMPLE SIZE

Default rates in term of NPL are drawn from a group of 33 Islamic banks operating in the country. The data covers the period from 2011 to 2015 on an annual basis. The study uses data of the macroeconomic indicators, which are growth of domestic product (GDP), exchange rate premium (EXR), and change in the money supply ($\Delta M2$), as well as financial and bank-specific variables, which are total assets (TAs), total deposits (TDs), and total loans (TLs) over the same period.

4. METHOD(S)

The analyses in the paper use panel data regression to assess the probability and exposure to default risk of the Islamic banking system in Sudan. The study employs binary choice models of probit and logit regression.

4.1. Panel Data Analyses

Panel data refer to datasets consisting of cross-sectional observations over time, or pooled cross-section and time series data. They have two dimensions, one for time and one for the cross-section entity. For the time dimension, a subscript t is used to stand for the time dimension, with $t = 1, 2, \dots, T$ for T observations at the T timepoints. For the cross-sectional data, the entity can be individuals, firms, regions, or countries. The subscript n to the variable is usually adopted to represent the cross-section dimension, with $n = 1, 2, \dots, N$ for N observations for N different entities. Statistically, a panel data can provide more observations to enjoy the large sample status, so the central limit theorem may apply where its respective single dimensional time series or cross-sectional dataset fails, making estimation and inference more efficient (Wang, 2009). Panel data regression is useful for assessing the relationship between the default rates (NPLs) of a group of entities (banks) during a certain time horizon and a group of macroeconomic, bank-specific, and financial variables.

4.2. Fixed Effects versus Random Effects

Pooled time series and cross-sections with both the time dimension and cross-section dimension can be expressed as follows:

$$y_{it} = X_{it}\beta + \omega_{it} \quad i = 1, \dots, N; \quad t = 1, \dots, T, \quad (1)$$

where

$$X_{it} = [x_{1it} + x_{kit}]_{(k \times 1)} \quad \text{and} \quad \beta = \begin{bmatrix} \beta_1 \\ \dots \\ \beta_k \end{bmatrix}_{(1 \times k)}.$$

A compact matrix representation for the panel is given as:

$$y_i = X_i\beta + \omega_i, \quad i = 1, \dots, N, \quad (2)$$

where

$$y_i = \begin{bmatrix} y_{i1} \\ \dots \\ y_{iT} \end{bmatrix}_{(T \times 1)}, \quad X_i = \begin{bmatrix} X_{i1} \\ \dots \\ X_{iT} \end{bmatrix} = \begin{bmatrix} x_{1i1} & \dots & x_{ki1} \\ \dots & \dots & \dots \\ x_{1iT} & \dots & x_{kiT} \end{bmatrix}_{(TK)}$$

and $\omega_{it} = \begin{bmatrix} \omega_{i1} \\ \dots \\ \omega_{iT} \end{bmatrix}_{(T \times 1)}$.

For any individual entity, y_i is a $(T \times 1)$ vector for T observations of the dependent variable, X_i is a $(T \times K)$ matrix of independent variables or regressors, with K being the number of independent variables, and β is a $(K \times 1)$ vector of coefficients. Finally, a compact matrix representation for the panel is given as:

$$y = X\beta + \omega, \tag{3}$$

$$y = \begin{bmatrix} y_1 \\ \dots \\ y_N \end{bmatrix}_{[(T \times N) \times 1]}, \quad X = \begin{bmatrix} X_1 \\ \dots \\ X_N \end{bmatrix}_{[(T \times N) \times K]} \quad \text{and} \quad \omega = \begin{bmatrix} \omega_1 \\ \dots \\ \omega_N \end{bmatrix}_{[(T \times N) \times 1]}$$

Various effects associated with the intercept can be formulated by decomposing ω_{it} in different ways. For individual effects, the fixed effects model assumes that

$$\omega_{it} = c_i + \varepsilon_{it}, \tag{4}$$

where c_i is individual-specific and time-invariant unobserved heterogeneity and is a constant for entity i , $\text{cov}(c_i, X_{it}) \neq 0$, $\text{Cov}(\varepsilon_{it}, X_{it}) = 0$, $\text{Var}(\varepsilon_{it}) = \sigma_\varepsilon^2$; and ε_{it} is pure residuals uncorrelated with each other and uncorrelated with independent variables. A compact matrix representation for the panel data model with fixed effects is given as:

$$y = c + X\beta + \varepsilon, \tag{5}$$

where

$$c = \begin{bmatrix} c_1 \\ \dots \\ c_N \end{bmatrix}_{[(T \times N) \times 1]}, \quad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \dots \\ \varepsilon_N \end{bmatrix}_{[(T \times N) \times 1]}, \quad c_i = \begin{bmatrix} c_1 \\ \dots \\ c_i \end{bmatrix}_{(T \times 1)}$$

and $\varepsilon_i = \begin{bmatrix} \varepsilon_{i1} \\ \dots \\ \varepsilon_{iT} \end{bmatrix}_{(T \times 1)}$.

Fixed effects models cannot be readily estimated by the Ordinary Least Square (OLS). There are few approaches that augment the OLS, such as resorting to dummies, applying first differencing over time, and performing the within transformation.

The random effect model with individual effects assumes that

$$\omega_{it} = \mu_i + \varepsilon_{it}, \tag{6}$$

where μ_i is a random variable, $E(\mu_i) = 0$, $\text{Var}(\mu_i) = \sigma_\mu^2$, $\text{Cov}(\mu_i, X_{it}) = 0$, $\text{Cov}(\mu_i, \varepsilon_{it}) = 0$, $E(\varepsilon_{it}) = 0$, $\text{Var}(\varepsilon_{it}) = \sigma_\varepsilon^2$; and ε_{it} are pure residuals uncorrelated with each other and uncorrelated with independent variables. A compact matrix representation for the panel data model with random individual effects is

$$y = X\beta + \mu + \varepsilon, \tag{7}$$

where

$$u = \begin{bmatrix} u_1 \\ \dots \\ u_N \end{bmatrix}_{[(T \times N) \times 1]}, \quad u_i = \begin{bmatrix} u_1 \\ \dots \\ u_N \end{bmatrix}_{[T \times 1]}, \quad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \dots \\ \varepsilon_N \end{bmatrix}_{[(T \times N) \times 1]}$$

$$\text{and } \varepsilon_i = \begin{bmatrix} \varepsilon_{i1} \\ \dots \\ \varepsilon_{iT} \end{bmatrix}_{[T \times 1]}.$$

4.3. Stationarity Test and Panel Unit Root Test

Panel unit root tests provide an overall aggregate statistic to examine whether there exists a unit root in the pooled cross-section time series data and judge the time series property of the data accordingly. It is claimed that the panel framework provides remarkable improvement in statistical power compared to performing a separate unit root for each individual time series (Wang, 2009).

4.4. The Logit Model

In a binary choice model, the dependent variable takes the value of either 1 or 0, with a probability that is a function of one or more independent variables. The logit model is commonly used to formulate binary choice, response, or categorization. The logit model derives its name from the logistic function. Regression for estimating the logit model is referred to as logistic regression.

The logit model is based on the odds of an event taking place. The logit of a number P between 0 and 1 is defined as:

$$\text{Logit}(P) = \text{Ln} \frac{P}{1-P}. \tag{8}$$

If $P = P(Y = 1|X\beta)$ is the probability of an event taking place, then $P/(1-P)$ is the corresponding odds and $\text{Ln}[P/(1-P)]$ is the corresponding log odds. The logit model states that the log odds of an event taking place are a linear function of a given set of explanatory variables, i.e.:

$$\text{Ln} \frac{P}{1-P} = X\beta. \tag{9}$$

The probability $P = P(Y = 1|X\beta)$ can be solved as:

$$P(Y = 1|X\beta) = \frac{\exp(X\beta)}{1 + \exp(X\beta)}. \tag{10}$$

Estimation of the logit models is usually through maximizing their likelihood function. Recall that the likelihood of a sample of N independent observations with probabilities P_1, P_2, \dots, P_N, L , is

$$L = P_1, P_2, \dots, P_N = \prod_{i=1}^N P_i. \tag{11}$$

For the logit model, the probability of Y being 1 is

$$P(Y = 1 | X\beta) = \frac{\exp(X\beta)}{1 + \exp(X\beta)}.$$

And the probability of Y being 0 is

$$P(Y = 0 | X\beta) = 1 - P(Y = 1 | X\beta) = 1 - \frac{\exp(X\beta)}{1 + \exp(X\beta)}.$$

Therefore, the likelihood function of the logit model, $L(\beta)$, is

$$L(\beta) = \prod_{i=1}^N \left[\frac{\exp(X_i\beta)}{1 + \exp(X_i\beta)} \right]^{y_i} \left[1 - \frac{\exp(X_i\beta)}{1 + \exp(X_i\beta)} \right]^{(1-y_i)}. \quad (12)$$

And the log-likelihood function of the logit model, $LL(\beta)$, is

$$LL(\beta) = \sum_{i=1}^N y_i \ln \left[\frac{\exp(X_i\beta)}{1 + \exp(X_i\beta)} \right] + (1 - y_i) \ln \left[1 - \frac{\exp(X_i\beta)}{1 + \exp(X_i\beta)} \right]. \quad (13)$$

Coefficient estimates can be derived, adopting procedures that maximize the earlier-mentioned log-likelihood functions.

5. RESULTS AND DISCUSSION

The study investigates the impact of key macroeconomic and financial indicators on the default rates of a sample of 33 Islamic banks in Sudan in the period 2011–2015.

To assess bank's probability of defaulting loans, the authors used probit and logit models. To convert the data into binary variables, they ranked (from highest to lowest) the ratio of NPL to TLs. Any bank with NPL/TL greater than the NPL/TL benchmark has been labeled as high-exposure risk. Benchmarks are identified using the average for all the banks on the sample. Any bank of high exposure is assigned the number 1, and otherwise is assigned the 0 value.

The recoverable loans (RLs; total loans – none performing loans) are expressed as X_1 , the TAs are expressed as X_2 , while X_3 stands for the TDs. The binary model of logit helps in assessing the likelihood of banks' exposure to credit risk and measures the impact of explanatory variables on the bank's risk exposure.

Then, the scenario analyses are applied by this study to assess the banks' resilience to the financial shocks or plausible events. Baseline scenarios have been developed for this purpose.

5.1. Panel Regression Analysis

To check stationarity of variables, the authors employed panel unit root tests for the dependent variable (NPL), and the independent variables (TD, TL, TA, GDP, EXR, and $\Delta M2$). Panel unit root tests results (not reported in the paper) cannot reject the null hypothesis of unit root at the level, but they reject the null hypothesis at the first difference of the variables. Hausman's test results show that the random effect model is the best fit model for the data, as indicated in Table 1. It accepts the null hypothesis that the random effect model is appropriate, and rejects the alternative hypothesis of the fixed effect model. The panel regression results from the random effect model are summarized in the Table 2. The results show the NPL is positively associated with GDP growth rate, EXR, change in TLs, and change in TAs. However, it is negatively associated with change in TDs and the change in the supply of money ($\Delta M2$). All banks' specific variables display significant relationship with the dependent variable. In contrast, the macroeconomic variables display

Table 1. Random Effects–Hausman Test.

Test Summary	Chi-Square Statistic	Chi-Square d.f.	Probability
Cross-section random	0.000000	6	1.0000

Table 2. Random Effect Regression Model.

Variable	Coefficient	t-Statistic	Probability
GDP	1168161.	0.171099	0.8644
EXR	24188902	0.215842	0.8294
ΔM2	−281.9161	−0.311091	0.7561
TA	0.030991	4.893143	0.0000
TD	−0.124662	−15.16774	0.0000
TL	0.147784	10.52069	0.0000
C	23912438	−0.176619	0.8600
Weighted statistics			
<i>F</i> -statistic		148.2436	
Prob(<i>F</i> -statistic)		0.000000	
Durbin–Watson statistic		1.596796	

Note: EXR is the exchange rate premium, ΔM2 is the change in the money supply, TAs represent the total assets, TDs represent the total deposits, and TLs represent the total loans.

insignificant relationship with the dependent variable. As a result, a 1% change in the TD variable affects negatively the NPLs by 12%. Whereas, the 1% change in TA and TLs affect the NPLs by 3% and 14%, respectively. Macroeconomic variables (GDP, EXR, and ΔM2) display an insignificant relationship with the dependent variables, which implies that only the bank-specific variables (TAs, TDs, and TLs) have a significant and important effect on the dependent variable NPL ratio.

5.2. Logit Regression Results

In the second stage of the analyses, the study uses the Logit regression model to assess the credit risk of default as well as the credit risk exposure. The study sets the probability of a default indicator NPL ratio (NPL/TL) as the dependent variable. The NPL ratio has been set as 1 or 0, by taking the average of the NPL ratio for all banks in each year and determining the average as a benchmark. Each bank with a value greater than the benchmark is scored 1; otherwise, it is 0. The bank’s specific variables like RLs, TAs, and TDs are defined as independent variables. The RLs have been taken as a proxy for managerial efficiency, i.e., the higher level of RLs, the better the managerial performance. The TAs and TDs represent bank size indicators; they reveal the effect of bank size on credit default or credit risk exposure.

Results in Table 3, indicate that the RLs variable (X_1) shows a negative relationship with banks’ default rates, whereas the TAs variable (X_2) is positively associated with the NPL ratio, implying that larger banks are more vulnerable to default risk. The deposits variable (X_3) shows a negative association with increase in default loans, indicating that banks with larger deposits have lower default risk, implying that Islamic banks in Sudan have lesser problems in managing their liabilities, as there are no interest obligations payable to deposit owners.

Table 3. Logit Regression (Dependent Variable: NPL Ratio)

Coefficient	Year 2011	Year 2012	Year 2013	Year 2014	Year 2015
X_1	-2.68E-06 **(0.26)	-2.33E-06 **(0.11)	-7.79E-06 **(0.03)	-1.10E-10 **(0.93)	-1.69E-09 **(0.38)
X_2	4.80E-06 **(0.04)	3.53E-06 **(0.08)	5.47E-06 **(0.04)	8.13E-10 **(0.34)	1.02E-09 **(0.11)
X_3	-4.30E-06 **(0.12)	-3.37E-06 **(0.11)	-1.93E-06 **(0.43)	-1.00E-09 **(0.38)	-1.05E-09 **(0.38)
Constant	-1.448 **(0.02)	-1.482 **(0.03)	-0.808 **(0.25)	-0.692 **(0.16)	0.227 **(0.73)
Marginal Effect					
X_1	-6.22E-07	-5.20E-07	-1.94E-06	-2.70E-11	-2.17E-10
X_2	1.11E-06	7.88E-07	1.37E-06	1.99E-10	1.32E-10
X_3	-9.96E-07	-7.51E-07	-4.82E-07	-2.46E-10	-1.35E-10
No. of observations	33	33	33	33	33

Note: X_1 represents the recoverable loans, X_2 represents the total assets, and X_3 represents the total deposits.

* Stands for 1% significant level, ** stands for 5% significant level, *** stands for 10% significant level.

6. CONCLUSION

In this paper, the authors employed panel data regression to assess the determinants of credit risk in the Islamic banking system, and then we set up the stress testing model to assess the exposure of these banks to credit risk pressure. The findings in the paper show credit risk as measured by NPLs is positively associated with GDP growth rate, EXR, change in TLs, and change in TAs. It is negatively associated with change in deposits (TDs) and the change in the supply of money ($\Delta M2$). All banks' specific variables display significant relationship with the dependent variable, which is the credit risk. In contrast, the macroeconomic variables display insignificant relationship with the dependent variable. The stress test results indicate larger banks in terms of assets face higher probabilities of credit defaults, and banks with higher deposits face lower probabilities of credit defaulting. The negative association between deposits and credit risk (default risk) reveals that Islamic banks have less problems in managing their liabilities as there is no interest payable to deposit owners.

Author Contributions

Both authors contributed equally to this study.

Conflict of Interest

None.

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